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ORIGINAL RESEARCH

Development of a clinical prediction model for high hospital cost in patients admitted for elective non-cardiac surgery to a private hospital in South Africa

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Introduction: Clinicians may find early identification of patients at risk for high cost of care during and after surgery useful, to prepare for focused management that results in optimal clinical outcome. The aim of the study was to develop a clinical prediction model to identify high and low hospital cost outcome after elective non-cardiac surgery using predictors identified from a preoperative self-assessment questionnaire.

Methods: Data to develop a clinical prediction model were collected for this purpose at a private hospital in South Africa. Predictors were defined from a preoperative questionnaire. Cost of hospital admission data were received from hospital administration, which reflected the financial risk the hospital carries and which could be reasonably attributed to a patient's individual clinical risk profile. The hospital cost excluded fees charged (by any healthcare provider), and cost of prosthesis and other consignment items that are related to the type of procedure. The cost outcome measure was described as cost per total Work Relative Value Units (Work RVUs) for the procedure, and dichotomised. Variables that were associated with the outcome during univariate analysis were subjected to a forward stepwise regression selection technique. The prediction model was evaluated for discrimination and calibration, and internally validated.

Results: Data from 770 participants were used to develop the prediction model. The number of participants with the outcome of high cost were 142/770 (18.4%). The predictors included in the full prediction model were type of surgery, treatment for chronic pain with depression, and activity status. The area under the receiver operating curve (AUROC) for the prediction model was 0.83 (95% confidence interval [CI]: 0.79 to 0.86). The Hosmer–Lemeshow indicated goodness-of-fit ($p = 0.967$). The prediction model was internally validated using bootstrap resampling from the development cohort, with a resultant AUROC of 0.86 (95% CI: 0.82 to 0.89).

Conclusion: The study describes a clinical risk prediction model developed using easily collected patient-reported variables and readily available administrative information. The prediction model should be validated and updated using a larger dataset, and used to identify patients in which cost-effective care pathways can add value.

Key points

Question: Which patient-reported predictors contribute to high cost of elective surgery?

Findings: Depression, chronic pain treatment and low activity status in combination with the type of surgical procedure, predict high cost.

Meaning: Patient-centred risk factors should be considered when determining the cost-effectiveness of surgical interventions.

Glossary of terms

SASA	South African Society of Anaesthesiologists
ASOS	African Surgical Outcomes Study
REDCap	Research Electronic Data Capture
TRIPOD	Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis
ZAR	South African Rand
RVU	Relative Value Unit
CCSA	Complete Current Procedural Terminology for South Africa
IQR	Interquartile range
AUROC	Area under the receiver-operating curve

MeSH terms

Hospital costs
Risk assessment
Private sector
Perioperative care

Introduction

Significance

Clinicians have limited access to aggregated data on clinical outcomes after surgery in the South African private healthcare sector. The lack of data impacts on efforts to improve the quality of care at a team (micro) or hospital (meso) level.[1] As the cost of health care increases, it is becoming more important to demonstrate value.[2] To demonstrate value, the quality of care has to justify the cost of care (value = quality/cost).[3] Improving the effectiveness of perioperative care by appropriate allocation of resources may reduce costs, therefore adding value from a patient, and funder perspective.

Background

Clinical prediction models are useful to summarise the influence of predictors, and their combined relationship, on a specific endpoint. They are used to identify predictors for an outcome from a specific patient setting, and also to determine a predicted estimate for a specific outcome in similar settings.[4] The ASOS Risk Calculator, developed from the African Surgical Outcomes

Study (ASOS)[5] cohort, is an example of a prediction model to identify patients at risk for severe complications and death.[6] Healthcare resource use has been used in clinical research as an outcomes measure,[7,8] but is not an endpoint commonly considered by perioperative clinicians when assessing risk. There is an opportunity for further research on the relationship of quality and cost in perioperative care, to inform the practice of the clinical team.[9] Tailoring healthcare resource use to a patient's individual risk profile may improve clinical outcomes after surgery – in other words, spending more on patients that need it may improve outcome.[10]

By defining predictors of outcome after surgery from a pre-operative self-assessment questionnaire (in this case hospital costs of admission episode), early risk stratification for scheduled (elective) surgery is possible. This is relevant in a healthcare system that does not support preoperative assessment clinics, and where admission on the day of planned surgery may be the first point of contact with anaesthesia providers. It may be important for a clinician to know in advance which patients may require a higher 'treatment intensity' to keep them safe during and after surgery.[10]

Aim

The aim of the study was to develop a clinical prediction model for hospital cost from a self-assessment questionnaire in patients admitted for elective surgery.

Objective

To identify risk factors (predictors) for high cost of surgery, and define the relationship between these predictors using a clinical prediction model.

Methods

The prospective data to develop a clinical prediction model were collected at a private hospital in South Africa from July to December 2015. Ethics approval was obtained from the University of Pretoria, Faculty of Health Sciences Research Ethics Committee. The requirement for written consent was waived. Permission for the study to be conducted was obtained from the hospital manager and the hospital group's Research Operational Committee.

All data were analysed using Stata®/IC 15.1 for Windows, StataCorp LLC, Texas, USA.

Source of data and participants

Patients 18 years and older presenting to the preadmission administration area for an elective non-cardiac, non-obstetric surgical intervention involving at least one postoperative night in hospital were eligible for recruitment to this observational study. Cases with missing data in outcomes, or cases where less than 90% of the questionnaire was completed, were excluded. Cardiac surgery patients were excluded, and the study focused on identifying predictors for non-cardiac surgery. Obstetric patients were excluded because of the healthier profile of women of childbearing age, and better outcomes after surgery. Patients had a choice to complete the preoperative measurement instrument as a paper-based or electronic self-assessment questionnaire. The questionnaire was translated from English to Afrikaans and offered as a paper-based tool in this language to patients on request. Pilot testing was performed before starting the study. Patients were provided with information in the questionnaire introduction, and consent was implied with completion of the questionnaire. The information sheet and form for the printed questionnaire are attached as supplementary material (Supplement 1).

In-hospital outcomes data (mortality, length of stay, ICU admission, cost) and procedural data were obtained from the hospital database (administrative data) using South African identity number as patient identifier. The outcomes and procedural data were temporally linked with the completion of the preoperative questionnaire. No data on perioperative care processes or clinical interventions were collected. Hospital cost reflected at least one day of hospital admission for all patients. Patients admitted to hospital more than 24 hours preoperatively were excluded because of the possibility of changes to patient health as reported in the questionnaire during admission.

Data was stored and managed electronically using Research Electronic Data Capture (REDCap®) software[11] installed on a Safe Surgery SA[12] server. This report was compiled according to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) guidelines.[13]

Outcomes

Cost of hospital admission was defined as total cost billed by the hospital in ZAR minus the fees and consignment items such as prosthesis, which reflect the cost risk that the hospital service provider carries (e.g. drug/dispensary costs, disposable costs and other additional costs). The cost was divided by the total Work Relative Value Units (Work RVUs), published in the Complete Current Procedural Terminology for South Africa (CCSA) as associated with the particular procedural codes. The CCSA is an adaptation of the American Medical Associations' Current Procedural Terminology (CPT). Work RVUs are used in the United States as a component in the determination of fees to physicians. It is an indication of physician work and reflects the complexity of a surgical procedure.[14]

Post hoc the outcome for cost was dichotomised – high cost cases being those with log transformed cost in ZAR per Work RVU of equal to and more than the mean of the transformed variable plus one standard deviation. This threshold was determined after data inspection, considering the distribution of the data with a long tail, as expected. In a normal distribution, if high cost is defined as mean plus one standard deviation, the 84th percentile gives this point. For $\log_e$ transformed cost/Work RVU, under the assumption of normality, the 84th percentile equals 8.197 which, on the original scale, translates into ZAR/Work RVU 3630 (= $e^{8.197}$). Summaries of the data on cost before and after transformation are presented in supplementary material (Supplement 2).

Predictors

Data were collected to define and identify preoperative predictors of poor postoperative outcome from a 141-item self-assessment questionnaire. Current evidence on predictors for any postoperative outcome measure (including mortality) was considered to define predictors from the questions (Supplement 3). Certain questions in the questionnaire were grouped to define a predictor. After data inspection, potential predictors were coded (i.e. categories defined for categorical and possibly continuous variables, as described by Steyerberg):[4] The decision on which coding to use for continuous variables was made based on the difference that either coding type made to model performance. Categories within variables were collapsed when the observed frequency in one of the categories was low, e.g. physical status self-assessment category 4 was combined with category 3. Multiple iterations of univariate analysis were performed to optimise predictor definitions when groups of questions were used to define a variable (different groupings of questions analysed), and to optimally code predictors.

Predictors were not considered when more than 5% of cases had missing data for such a variable, since patients were unlikely to report on such data in future research (e.g. calculated body mass index). Patient variables were not considered candidate predictors if the incidence was low in the sample population, it showed no association with the outcome during univariate regression, and/or the clinical significance of the predictor was judged low. Type of surgery was derived from the CPT codes captured as administrative data.

Sample size and missing data

The number of possible predictors as defined in the study protocol was 46. For logistic regression, an event per variable rate of at least 10 should be used when determining the number of predictors to be entered during model specification.[4]

An "available case analysis" was performed while analysing predictors, and no imputation was done for missing data.

Statistical analysis

Categorical variables were described as proportions and compared using Fisher's exact test. Continuous variables were described as mean and standard deviation, or median and interquartile range (IQR), and compared using t-tests.

The univariate association of cost with each of the defined predictors was assessed. Forward stepwise logistic regression was then employed to select variables after univariate testing, on all variables that were deemed clinically relevant, at a significance level of 0.05.

The clinical prediction model for cost was specified using logistic regression technique. The model performance was evaluated for discrimination by determining the area under the receiver operating curve (AUROC), or c-statistic, with 95% confidence intervals (CIs), and for calibration by plotting observed against expected outcome with locally weighted scatterplot smoothing (LOWESS). A decision-curve analysis[15] was performed (not reported here). The model was internally validated using bootstrap resampling, where samples for validation are drawn and replaced in the development sample.[4,16]

Results

Participants

Nine hundred and sixteen patient records were collected. Patients admitted more than twenty-four hours before surgery were excluded. Exclusions were as follows: admission more than 24 hours before surgery (21 cases), incomplete questionnaire (117 cases) and two cases due to surgical procedures (cardiac or obstetric surgery). Two cases were excluded prior to univariate analysis, where total cost in ZAR or total Work RVUs reported did not match, based on inspection and clinical interpretation (Supplement 4). The final sample population size was 770 cases. There were 142/770 (18.44%) cases identified with the outcome (high cost). The flow of patients through the study is described in Figure 1. The characteristics of the patients in the cohort are described in Table I, with the number of records with missing data in predictors included.

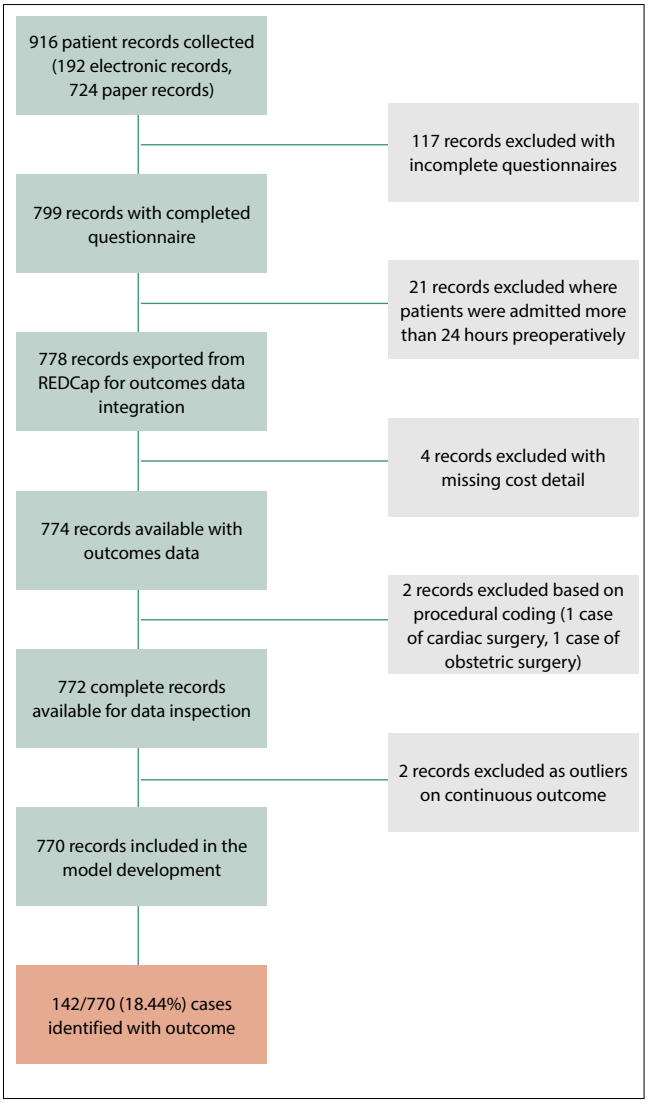

Figure 1: Diagram illustrating flow of patients through the study

Table I: Characteristics of the patients in the cohort before exclusion of patients with extreme values for cost

Characteristic (*n* = 772)	Frequency *n* (%)
Age category (Missing = 0)	
< 35 yrs	136 (17.62)
35–44 yrs	142 (18.39)
45–54 yrs	152 (19.69)
55–64 yrs	189 (24.48)
≥ 65yrs	153 (19.82)
Sex (Missing = 0)	
Male	324 (41.97)
Female	448 (58.03)
Race (Missing = 12)	
Black	43 (5.66)
White	690 (90.79)
Asian	16 (2.11)
Mixed	11 (1.45)
Physical status self-assessment (Missing = 0)	
Healthy	392 (50.78)
Illness affecting daily life mildly	312 (40.41)
Illness affecting daily life severely	64 (8.29)
Illness is a constant threat to life	4 (0.52)
Body mass index (Missing = 52)	
< 25	172 (23.89)
≥ 25	250 (34.72)
≥ 30	164 (22.78)
≥ 35	77 (10.69)
≥ 40	30 (4.17)
≥ 45	27 (3.75)
Hypertension (Missing = 0)	255 (33.03)
Diabetes (Missing = 0)	
Not using insulin	60 (7.77)
Using insulin	18 (2.33)
Smoking (Missing = 0)	
Previous smoker	147 (19.04)
Current smoker	151 (19.56)
Ischaemic heart disease (Missing = 0)	67 (8.68)
Metabolic syndrome (Missing = 0)	103 (13.34)
HIV-positive (Missing = 0)	28 (3.63)
History of tuberculosis treatment (Missing = 0)	12 (1.55)
History of VTE (Missing = 0)	45 (5.83)
Reported current renal impairment (Missing = 0)	15 (1.94)
Previous admission to hospital for lung disease (Missing = 0)	61 (7.90)
Current cancer treatment (Missing = 0)	13 (1.68)
Obstructive sleep apnoea risk (Missing = 0)	86 (11.14)
Previous stroke (Missing = 0)	23 (2.98)
Valvular heart disease (Missing = 0)	37 (4.79)
Reported 'weak heart' (Missing = 1)	38 (4.28)
Frail[17] (Missing = 0)	22 (2.85)
Hypothyroidism (Missing = 1)	124 (16.08)
Previous surgery for same problem (Missing = 10)	34 (4.46)
Low-dose aspirin use (Missing = 2)	169 (21.95)
Recent URTI or fever (Missing = 1)	129 (16.73)
Reported recreational drug use (Missing = 3)	15 (1.95)
Anabolic steroid use (Missing = 3)	15 (1.95)
Reported herbal medication use (Missing = 5)	122 (15.91)
Previous reaction to an anaesthetic or anaesthesia-related complication (Missing = 2)	107 (13.90)
Family history	
Malignant hyperthermia (Missing = 3)	1 (0.13)
Scoline apnoea (Missing = 4)	16 (2.08)
Porphyria (Missing = 9)	11 (1.44)
Type of surgery (Missing = 0)	
Neurosurgery	17 (2.20)
Spinal surgery	40 (5.18)
Orthopaedic surgery	205 (26.55)
Ear, nose and throat, head and neck surgery	42 (5.44)
Thoracic surgery	16 (2.07)
Vascular surgery	48 (6.22)
Upper GIT surgery	243 (31.48)
Lower GIT surgery	53 (6.87)
Genitourinary surgery	68 (8.81)
Plastic and breast surgery	38 (4.92)
Other surgery	2 (0.26)
Health literacy (confidence filling forms) (Missing = 5)	
Extremely confident	508 (66.23)
Quite confident	187 (24.38)
Somewhat confident	56 (7.30)
A little bit confident	12 (1.56)
Not at all confident	4 (0.52)
Inadequate information received on what to expect (Missing = 6)	30 (3.92)

CI – confidence interval, HIV – human immunodeficiency virus, VTE – venous thromboembolism, URTI – upper respiratory tract infection, GIT – gastrointestinal tract

Type of surgery was the only available procedure-related variable that was analysed as an independent variable. It was coded as a nominal variable. The type of surgery variable categories were created as follows: upper gastrointestinal surgery was taken as the reference category, since the cases in this category contributed to 31.6% (*n* = 243) of the total cohort. After univariate logistic regression, we grouped plastic, breast, ENT and head and neck surgery since these all had similar odds ratios for high cost. The number of categories were reduced from eleven to eight.

Model development

The data were insufficient to identify clinical predictors for length of hospital stay and ICU stay from the questionnaire. Mortality in the cohort was 0.26% (2/770). Cost was therefore chosen as the primary outcome post hoc.

After univariate regression analysis, predictors deemed clinically relevant were subjected to a stepwise regression selection if the *p*-value in univariate analysis was less than 0.05.

The twenty-two variables as defined during the coding process that were included in stepwise selection, are described in Table II.

Table II: Univariate analysis of variables that were subjected to stepwise regression selection. Data are mean (SD) or *n* (%)

Variable	All cases (*n* = 770)	Univariate analysis OR (95% CI)	*p*-value
Age *n* = 770	50 (15.3)	1.03 (1.02 to 1.05)	< 0.001
Pack years (current or past smoker) *n* = 770	5.5 (12.1)	1.01 (1.00 to 1.03)	0.014
Activity Status Score (maximum 23.45) *n* = 770	21.29 (4.4)	0.92 (0.88 to 0.95)	< 0.001
Physical status self-assessment *n* = 770			
Healthy	391 (50.8%)	**Reference**	
Illness affecting daily life mildly	311 (40.4%)	1.01 (0.67 to 1.52)	0.030
Illness affecting daily life severely, or a constant threat to life	68 (8.83)	2.465 (1.375 to 4.417)	0.002
Hypertension *n* = 770	254 (33.0%)	1.93 (1.31 to 2.83)	0.001
Low-dose aspirin use *n* = 770	169 (22.0%)	1.78 (1.17 to 2.70)	0.007
Previous surgery for the same problem *n* = 770	34 (4.5%)	2.15 (1.00 to 4.61)	0.050
Indication for surgery affects life severely *n* = 770	51 (6.6%)	2.71 (1.46 to 5.02)	0.002
Hypothyroidism *n* = 770	124 (16.1%)	1.66 (1.04 to 2.65)	0.033
Short-lived limb weakness or blindness not presenting for vascular surgery *n* = 770	11 (1.1%)	4.28 (1.29 to 14.25)	0.018
Depression self-assessment and on treatment for chronic pain *n* = 770	36 (4.7%)	4.96 (2.50 to 9.89)	< 0.001
Frailty *n* = 770	22 (2.9%)	2.40 (0.96 to 6.00)	0.062
Type of surgery *n* = 770			
Upper GIT	245 (31.8%)	**Reference**	
Neuro and spinal	57 (7.4%)	6.72 (2.05 to 22.03)	0.002
Orthopaedic	205 (26.6%)	33.32 (13.17 to 84.31)	< 0.001
Thoracic	16 (2.1%)	6.86 (1.22 to 38.59)	0.029
Vascular	48 (6.2%)	24.00 (8.23 to 69.95)	< 0.001
Lower GIT	53 (6.9%)	6.13 (1.79 to 20.91)	0.004
Genito-urinary	68 (8.8%)	3.81 (1.07 to 13.57)	0.039
Plastic, breast, ENT, head and neck	78 (10.1%)	2.59 (0.68 to 9.91)	0.163

OR – odds ratio, CI – confidence interval, GIT – gastrointestinal tract, ENT – ear, nose and throat. Variable definitions are available in supplementary material

Model specification

Following stepwise selection, a prediction model with 10 predictors resulted. The logit, g(**x**), of the multivariable logistic regression prediction model is presented in Table III reporting the estimated regression coefficients for the 10 binary variables and the model intercept. The observation vector of the 10 binary variables is **x** = (Upper GIT and other surgery, neuro and spinal surgery, orthopaedic surgery, thoracic surgery, vascular surgery, lower GIT surgery, genito-urinary surgery, plastic, breast, ENT and head and neck surgery, depression and on chronic pain treatment) and the probability of high cost is $p = \exp[g(\mathbf{x})]/[1+g(\mathbf{x})]$.

Model performance

The *discrimination* of the full prediction model was assessed from the AUROC, 0.83–95% CI: 0.79 to 0.86. (i.e. the model predicts 83% of the observed variability in the outcome). The Hosmer–Lemeshow statistic indicated goodness-of-fit ($p = 0.967$).

The *calibration* of the prediction model was assessed by plotting observed against expected outcomes, using Lowess smoothing. The validation plot is shown in Figure 2. Green circles indicate groups of patients with similar predicted risk. The distribution of subjects is indicated using red bars at the bottom of the plot: patients with the outcome above the x-axis, and those without the outcome below the x-axis. The visual display of agreement between observed and expected outcomes using a smoothing technique, is indicated by the blue line. The agreement is good up to values of around 0.60, after which the model underestimates risk. Of note is that the agreement of observed outcome and predictions in certain groups of patients with similar predicted risk is poor – the green circles falling away from the dashed reference line of perfect agreement. However, the distribution of subjects with regard to predictions shows a wide spread in patients with and without the outcomes, illustrating the ability of the model to perform with regards to discrimination.

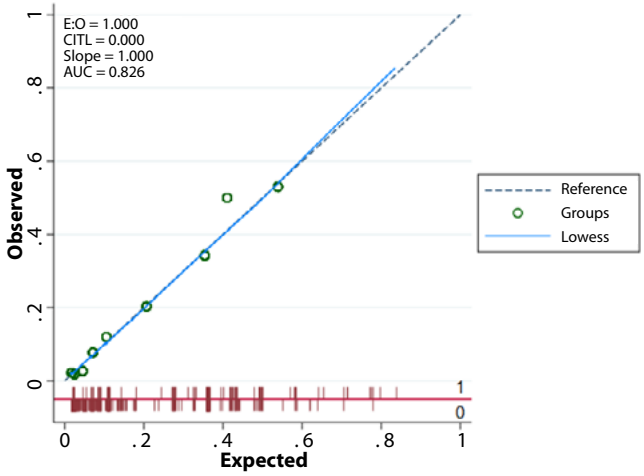

Figure 2: Calibration plot for full prediction model with binary cost outcome
E:O – expected:observed, CITL – calibration-in-the-large, Slope – slope beta, AUC – area under receiver operating curve (c-statistic)

Table III: Regression coefficients for the 10 binary variables included in the full clinical prediction model for the binary cost outcome

Variable	Regression coefficient	95% confidence interval	$p > \|z\|$
Intercept	-2.7489	-4.0668 to -1.4311	< 0.001
Type of surgery			
Upper GIT and other surgery	**Reference**		
Neuro and spinal surgery	1.6188	0.3793 to 2.8583	0.010
Orthopaedic surgery	3.4483	2.5156 to 4.3809	< 0.001
Thoracic surgery	1.9026	0.1674 to 3.6378	0.032
Vascular surgery	3.0476	1.968 to 4.1272	< 0.001
Lower GIT surgery	1.9084	0.6757 to 3.1412	0.002
Genito-urinary surgery	1.3615	0.0843 to 2.6386	0.037
Plastic, breast, ENT and head and neck surgery	0.9997	-0.3469 to 2.3462	0.146
Depression and on chronic pain treatment	0.9107	0.0717 to 1.7497	0.033
Activity status count	-0.0549	-0.1020 to -0.0077	0.023

GIT – gastrointestinal tract, ENT – ear, nose and throat

When the probability of high cost, $p = \exp[g(\mathbf{x})]/[1+ g(\mathbf{x})]$, was binarised using the cut-off 0.225, the most favourable combination of sensitivity (79.7%) and specificity (75.7%) resulted when compared to the true cost when binarised.

The full prediction model was internally validated using bootstrap resampling of the development cohort. The resulting AUROC was found to be 0.86 (95% confidence interval: 0.82 to 0.89).

Discussion

The study identified a combination of clinical predictors for high cost during and after elective surgery: type of surgery, and patient risk factors relating to reduced physical activity, and chronic pain medication use with depression.

The sample population is representative of the medically insured population of South Africa – a comparatively small part of the population consuming about half of total healthcare expenditure. The fact that administrative or billing data are meticulously collected in this environment enables reliable calculation of the cost of surgical intervention. The information can therefore be used to inform on cost-effectiveness of perioperative care. Cost-effective care should be offered to patients in both South African healthcare sectors, however, the model developed here will not be generalisable to the public sector.

Pre-surgery depression and lower self-efficacy were shown to be associated with poorer quality of life, health status and personal well-being in the two years following colorectal cancer surgery.[18] These risk factors are not commonly addressed in the perioperative period. Functional capacity assessment and exercise testing are well described in risk assessment for clinical outcomes.[19] Early preoperative patient engagement and risk screening can enhance risk management and perioperative planning, and add value to perioperative care if the economic impact of care is considered.[20]

The clinical prediction model may be presented, once externally validated, in electronic format following the capturing of predictors on a patient platform or portal. It may then be possible to devise and test best practice protocols for quality care in patients with reduced physical activity, depression and chronic pain, once they have been identified. Preoperative planning for perioperative pain management, psychological support, and pre-habilitation to improve functional status, may be considered. Such interventions require a multidisciplinary approach. Early electronic sharing of information, as soon as the decision to consider surgery has been made, may allow for appropriately timed preoperative intervention, or postponement of surgery to optimise patient status.

Electronic patient portals facilitate data collection from patients and improve information exchange between patients and the members of the clinical team involved with their care.[21] Subsequent to completing a questionnaire, patients can be involved in shared decision-making and the reporting of endpoints after surgery encouraged.[22,23] An updated prediction model can in the future be presented as part of a decision tree on the need for preoperative anaesthesia consultation, risk management and quality improvement projects.[4]

It is crucial to consider patient-centred/patient-reported outcomes measures as endpoints when answering questions on the value of perioperative care (e.g. in cost-utility analysis).[24] By understanding the impact of surgery on quality of life, and tailoring cost-effective care to this patient-centric measure, much value can be added.[23,25]

There is also a need to validate well-known predictive scores/indices/calculators for mortality and other clinical outcomes in the SA private healthcare population, should more clinical data become available from this sector. Further efforts to adjust for procedure mix, to allow for a universal prediction or risk stratification tool, should be made.[26–30] This can only happen once larger volumes of information on heterogeneous surgical procedures are made available.

There are limitations to the study. First, the objective of the study was to determine which predictors for high cost are important, and the prediction model cannot be used to determine absolute risk for high cost without external validation. Second, a number of issues related to development will impact on usefulness of the prediction model. The iterative approach used to select variables for model specification may have resulted in a model that fits the data well, but introduces bias and contributes to model uncertainty.

Stepwise selection methods can lead to overestimation of model performance if the event rate is low.[4] Internal validation with bootstrap resampling may not sufficiently address the problem of optimism with model performance. Overfitting of the model is a central problem with this relatively small cohort and a larger number of potential predictors. Validation in new patients is required. Future attempts at external validation in new patients may require significant updating of the prediction model. Updating will also be required in response to changes in the observations (for example, due to changes in clinical practice). With regular updating, so-called 'dynamic' prediction models can be created.[31,32]

Third, several factors impact on the representativeness of the sample. Recruitment bias is likely since it was not possible to screen all consecutive patients for eligibility during the study period. The cohort was recruited at a single centre, and individual clinician preferences may have had a significant impact on the endpoint measured. The population may be representative of private healthcare recipients but not of the larger South African population. Ninety-one per cent of the patient cohort in this study was white (according to StatsSA, 10.4% of the Black African population with chronic disease had access to medical aid in 2017, compared to 71.4% of the white population). English language literacy, health literacy and comfortable use of digital applications were required for most patients to participate.

Fourth, no imputation of missing data was done. 'Available case analysis' is considered statistically inefficient – if subjects are ignored in the estimation of the regression model because of missing data for a variable, the number of events per variable may drop to a level where the modelling is unreliable.[33] Fifth, the binary outcome for cost that was used is relatively complex in its definition. However, it is not uncommon in the literature to decide on a high cost threshold of 75% of maximum cost when dichotomising the outcome.[33] Sixth, should all procedural codes, from which the Work RVUs are derived, not be captured per case, the degree of surgical complexity may be underestimated by the summed or total Work RVUs. This is important as preoperative risk factors and surgical complexity are more effective predictors of cost than complications.[14] Clinicians and hospitals in South Africa may not be capturing all relevant procedural codes consistently. Seventh, the sample size in this study was not sufficient to evaluate clinical predictors for high cost in specific types of surgery such as orthopaedic surgery.

This study contributes to the understanding of clinical predictors for increased cost of care as reported by patients.

Conclusion

The clinical prediction model that was developed identifies predictors for high cost of perioperative care in the private SA sector. External validation will allow its use by clinicians to identify patients in which perioperative management should be tailored to ensure quality of care.

This study highlights the contribution perioperative research in the South African private healthcare sector can make in an economically fragile and fragmented healthcare system. There exists a dearth of cost-effectiveness research in anaesthesiology,[9] and research in this field can contribute significantly to understanding the clinical options for high quality perioperative care.

Unnecessary expenditure has to be curtailed, but healthcare providers may have to work harder to demonstrate the value of surgical intervention in patients with risk factors for high cost.[34-36] This would be of benefit to plan delivery of universal health coverage to the larger South African population.[37,38]

Conflict of interest

The authors declare no conflict of interest.

Funding source

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Ethical approval

Ethics approval for the study was obtained from the University of Pretoria, Faculty of Health Sciences Research Ethics Committee, reference number 489/2014.

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Supplementary files available online:

Supplement 1: ***Patient information and self-assessment questionnaire***

Supplement 2: ***Binary outcome definition***

Supplement 3: ***Table – Use of self-assessment questions to define predictor variables***

Supplement 4: ***Table – Information on cases with extreme values excluded from derivation cohort***