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Few and feasible preoperative variables can identify high-risk surgical patients: derivation and validation of the Ex-Care risk model

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Abstract

Background: The development of feasible preoperative risk tools is desirable, especially for low-middle income countries with limited resources and complex surgical settings. This study aimed to derive and validate a preoperative risk model (Ex-Care model) for postoperative mortality and compare its performance with current risk tools.

Methods: A multivariable logistic regression model predicting in-hospital mortality was developed using a large Brazilian surgical cohort. Patient and perioperative predictors were considered. Its performance was compared with the Charlson comorbidity index (CCI), Revised Cardiac Risk Index (RCRI), and the Surgical Outcome Risk Tool (SORT).

Results: The derivation cohort included 16 618 patients. In-hospital death occurred in 465 patients (2.8%). Age, with adjusted splines, degree of procedure (major *vs* non-major), ASA physical status, and urgency were entered in a final model. It showed high discrimination with an area under the receiver operating characteristic curve (AUROC) of 0.926 (95% confidence interval [CI], 0.91–0.93). It had superior accuracy to the RCRI (AUROC, 0.90 *vs* 0.76; $P<0.01$) and similar to the CCI (0.90 *vs* 0.82; $P=0.06$) and SORT models (0.90 *vs* 0.92; $P=0.2$) in the temporal validation cohort of 1173 patients. Calibration was adequate in both development (Hosmer–Lemeshow, 9.26; $P=0.41$) and temporal validation cohorts (Hosmer–Lemeshow 5.29; $P=0.71$).

Conclusions: The Ex-Care risk model proved very efficient at identifying high-risk surgical patients. Although multicentre studies are needed, it should have particular value in low resource settings to better inform perioperative health policy and clinical decision-making.

Keywords: mortality; postoperative mortality; preoperative risk assessment; risk assessment; surgery; validation model

Editor's key points

- Accurate risk prediction in surgery is needed for patient and clinician decision-making.
- Many surgical risk tools require detailed clinical and laboratory data to estimate outcome probabilities, or have not been validated in a variety of healthcare settings.
- High-risk patients can be accurately identified by the Ex-Care model, which requires only preoperative data variables.
- Ex-Care risk prediction may be particularly useful in low resource settings, such as in many low- and middle-income countries.

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Both postoperative morbidity and mortality vary among patients, being higher in particularly vulnerable groups of high-risk patients.[1,2] Therefore, accurate identification of high-risk patients is strongly recommended[3,4] and part of the concept of perioperative re-engineering: the optimisation of processes by timely engagement of patients, caregivers, and structure.[5,6] The feasibility of reliable risk assessment is particularly important when considering the breadth of global healthcare, where resources are constrained, especially in low- and middle-income countries (LMICs) where primary care is insufficient and advanced conditions of diseases compound the surgical scenario.

The recently published SAMPE (Serviço de Anestesia e Medicina Perioperatoria) model,[7] designed to predict postoperative in-hospital deaths in a single centre in southern Brazil, encompasses the characteristics of an ideal risk model: parsimony, extreme accuracy, and few and sustainable variables (age; American Society of Anesthesiologists physical status [ASA-PS] classification; surgical severity – minor, intermediate or major; and surgical nature – urgent or elective). Its introduction in clinical practice reduced the rapid response team calls within 30 postoperative days in the high-risk patient group who underwent a PACU postoperative pathway (Gutierrez, unpublished observations, 2020). Better categorisation of surgical procedures would, however, ameliorate the interface of the model. Moreover, value could be supported by comparing its performance with other established risk tools.

Our aim was to develop a feasible preoperative risk assessment tool based on the SAMPE model (the Ex-Care model) to predict postoperative mortality in a large Brazilian cohort. We also compared its performance with several current risk assessment tools such as the ASA-PS,[8] the Charlson comorbidity index (CCI),[9] the Risk Cardiac Revised Index (RCRI),[10] and the Surgical Outcome Risk Tool (SORT) model,[11] which was designed to evaluate mortality prediction. Our findings may ground the development of pragmatic models in LMICs where extrapolation of risk prediction tools should be done with caution, considering the specifics of each health system.

Methods

Data source and study population

The model was entirely developed using the derivation dataset, collected based on the electronic health record data from in-patient registries from January 1, 2016 to December 31, 2017. The Ex-Care model's performance compared to other risk models was evaluated in a subsequent sample collected from January 1 to July 31, 2018. We analysed data from patients aged 16 yr or older who underwent surgery with anaesthesia. Patients undergoing diagnostic, cardiac, obstetric, or organ transplantation procedures were not included. When more than one surgery was performed during the same hospital admission, only the major one was analysed. Written informed consent was not required, although a confidentiality agreement was signed to access the institution's database. Ethical approval was obtained from the Hospital de Clínicas de Porto Alegre Postgraduate Research Group (Project number: 16-0229).

Outcome definition

The primary outcome was in-hospital death within 30 days.

Predictors and variables adjustments

The Ex-Care model was based on the original SAMPE model[7] built by the same authors of the present study. Sequential variables adjustments were fitted on the derivation sample and new coefficients were obtained, based on the same few predictors (age, ASA-PS, extent of surgery, and type of surgery) to keep with the principles of a parsimonious model.[12]

In the original SAMPE model, we classified procedures into major, intermediate, or minor degree, using a categorisation scheme based on literature review[13] and expert opinions, who considered surgical time, trauma, and predicted bleeding. However, there was no significant difference in the odds ratio (OR) from intermediate to minor degree. Thus, surgical degree was reclassified into two categories: non-major and major. Moreover, we carried out sequential adjustments to fit a non-linear function relationship between age and the primary outcome.[14–16]

Sample size and missing data

Our 2-yr consecutive sample and the anticipated number of deaths exceeded the calculated sample needed to develop a predictive model with four variables or six parameters and precluded the usual limitations related to overfitting.[17] We planned a *post-hoc* power analysis to confirm the adequacy of the sample size.

Model validity and comparison performance

We carried out the temporal validation of the Ex-Care model with a second sample that differed from the derivation cohort. We compared the accuracy of Ex-Care to current preoperative risk scores for general mortality such as ASA-PS,[8] the CCI,[9] a risk score for cardiac mortality, the RCRI,[10] and a mortality risk prediction model recently developed in the UK, the SORT model.[11] Variables needed to calculate each model were compiled. In Charlson's original method, scores were based on a weighted measure that incorporates age and 19 different medical diseases.[9,18] The modified RCRI was calculated by weighing the number of comorbidities: RCRI Class I, 0.4%; Class II, 0.9%; Class III, 2.4%; Class IV, 5.4%.[9] To calculate the SORT, the website http://www.sortsurgery.com/ was used.[19] Data on patient characteristics and perioperative factors were collected by trained research staff. Postoperative outcomes and the Postoperative Morbidity Survey (POMS)[20] on postoperative days 3 and 7 were obtained from review of the electronic records. The preoperative probabilities of death according to the four risk indexes were calculated for each patient. This study followed the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) statement (Supplementary file S1).[21]

Statistical analysis

Sequential adjustments were done and a final regression logistic model was obtained with four predictors variables: ASA-PS, surgical degree (major *vs* non-major), surgical nature (elective or urgent), and age. Calibration was assessed visually by plotting the observed *vs* predicted deaths. The overall performance of the model was measured with the Brier score,[22] and internal validation was performed using a bootstrap method, a statistical technique in which data were analysed in repeated sampling that resulted in similar but different populations. We subsequently assessed the improvement in the

Table 1 Descriptive data for the total study population. Values are numbers (proportion). ASA, American Society of Anesthesiologists.

	Derivation sample	
	Study population total n=16 618 (100%)	Deaths total n=465 (2.8%)
Age (yr)		
16–35	2734 (16.5%)	23 (5.0%)
36–55	5480 (33.0%)	95 (20.4%)
56–75	6985 (42.0%)	234 (50.3%)
>75	1419 (8.5%)	113 (24.3%)
Sex		
Male	7366 (44.3%)	238 (51.2%)
Female	9252 (55.7%)	227 (48.8%)
ASA physical status		
1	2779 (16.7%)	2 (0.4%)
2	9033 (54.4%)	42 (9%)
3	4206 (25.3%)	178 (38.3%)
4	528 (3.2%)	186 (40%)
5	72 (0.4%)	57 (12.3%)
Surgical nature		
Elective	13 275 (79.9%)	132 (28.4%)
Urgent	3343 (20.1%)	333 (71.6%)
Surgical severity		
Minor	6093 (36.7%)	79 (17.0%)
Intermediate	5792 (34.8%)	85 (18.3%)
Major	4733 (28.5%)	301 (64.7%)
Surgical specialty		
Urologic	2923 (17.6%)	37 (8.0%)
Digestive	2673 (16.1%)	123 (26.5%)
General	2489 (14.9%)	83 (17.8%)
Orthopaedic	1554 (9.4%)	22 (4.7%)
Gynaecological	1458 (8.8%)	1 (0.2%)
Otorhinolaryngologic	1155 (6.9%)	6 (1.3%)
Cardiovascular	1008 (6.0%)	48 (10.3%)
Vascular	828 (4.9%)	51 (11.0%)
Neurosurgery	575 (3.5%)	53 (11.4%)
Coloproctology	515 (3.1%)	14 (3.0%)
Mastology	500 (3.0%)	0 (0%)
Thoracic	457 (2.8%)	27 (5.8%)
Plastic	375 (2.3%)	0 (0%)
Oral–maxillofacial	97 (0.6%)	0 (0%)
Paediatric	11 (0.1%)	0 (0%)

Ex-Care model fit compared with the original model (SAMPE model) by quantifying the reassignments through the Net Reclassification Index (NRI).

Goodness-of-fit was verified for Ex-Care and SORT models through the Hosmer–Lemeshow test both in derivation and in the temporal validation sample. Discrimination of the Ex-Care model was assessed using the area under the receiver operating characteristic curve (AUROC). We considered an AUROC of <0.7 to indicate poor performance, 0.7–0.9 moderate, and >0.9 high performance.[23] To test the differences between two ROC curves, the DeLong test was used.[24]

Clinical usefulness

The resulting 30 day in-hospital mortality probability was categorised into four classes in order to be easily applied at the bedside: Class I, <2%; class II, 2–5%; class III, 5–10%; class IV, >10%. Classes III and IV were considered as high-risk surgical patients.[25]

We also undertook a Cox proportional hazards modelling in which the dependent variable was in-hospital death. The risk classes on the Ex-Care model were considered the independent predictors of the primary outcome and we determined the adjusted hazard ratio and the 95% confidence intervals for each risk class. Furthermore, to identify association between Ex-Care risk class and POMS domain[20] in the temporal validation cohort, a Poisson regression model with robust error variances[26] was performed. All tests were two-tailed, and alpha set at 0.05 denoted statistical significance. R studio (version 3.6.0) and SAS software version 9.4 were used for the statistical analyses.

Results

During the 24 months of analysis, 16 618 patients comprised the dataset used to develop the Ex-Care model. We excluded patients who received only local anaesthesia or underwent diagnostic procedures. In this series, there were 465 postoperative deaths (2.8%). Table 1 describes the characteristics of the derivation sample and Supplementary file S2 shows the study flow diagram.

Model development and predictive performance

Variables adjustments were sequentially done to build a consistent model. The procedures were classified into major *vs* non-major.[7] This simplified the great variability of procedures classification (Supplementary file S3 shows the procedures categorisation). However, the variable age showed a nonlinear distribution, and it entered in the model with adjusted splines (Supplementary file S4 shows the Odds of death as a function of age). Also, the variable ASA-PS was mathematically treated as approximately continuous, as using ASA-PS with five categories or two combined categories lead to unstable models. The coefficients of the new model are presented in Table 2 and the full equation in Supplementary file S5.

The AUROC for in-hospital mortality in the development cohort was 0.926 (95% confidence interval [CI], 0.91–0.93). The Hosmer–Lemeshow goodness-of-fit statistic was of 9.26 (P=0.41), which reflected an acceptable model calibration. Also, the Brier score result of 0.019 confirmed its excellent overall performance. The calibration plot is shown in Figure 1, and the

Table 2 Variables included in the new model (Ex-Care) with respective odds ratios and confidence intervals after variables adjustments (n=16 618). NS, non-significant.

Variable	Odds ratio	95% confidence interval	P-value
Age, yr (splines) 17 (ref)	1.00	1.00	
30	1.09	0.55–2.16	NS
50	1.38	0.55–3.45	NS
60	1.84	0.80–4.26	NS
70	2.70	1.11–6.52	<0.01
80	3.78	1.58–9.01	<0.01
90	5.27	2.12–13.11	<0.01
ASA-PS	6.66	5.65–7.84	<0.0001
Major *vs* non-major	1.69	1.35–2.13	<0.0001
Status (non-elective *vs* elective)	4.25	3.36–5.37	<0.0001

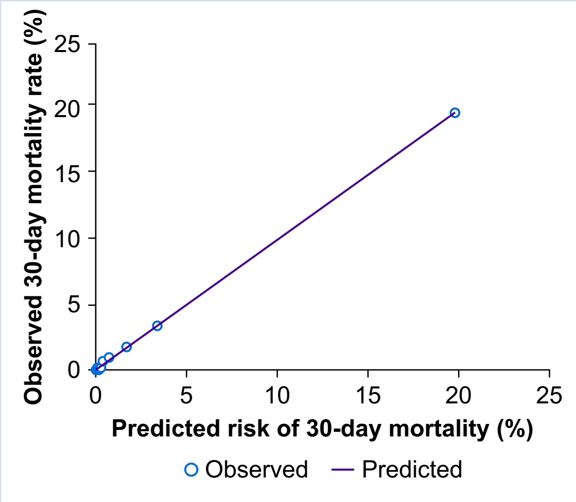


Fig 1. Observed *vs* predicted 30-day mortality at varying levels of risk. Circle size corresponds to the proportion of patients at each level of risk.

observed *vs* expected events for deciles of risk are presented in Supplementary file S6. The bootstrapping procedure that was carried out for internal validation provided AUCs varying from 0.904 to 0.948 for each generated sample, demonstrating an excellent predictive capacity. The c-statistic corrected for optimism was 0.925, with average optimism of 0.0004.

The hazard ratio point estimates for each risk class category as shown in Table 3 confirmed a progressive increase in risk of death as the Ex-Care risk class rose (being risk class I the index). Also, by changing the classification categories, we assessed the improvement in model fit from the original SAMPE model to the Ex-Care model. The categorical NRI was 0.025 (95% CI, 0.004–0.047; P=0.023), identified an improvement of 1.72% in those that died and of 0.78% in those that survived (Supplementary file S7). With the risk categories of <2%, 2–5%, 5–10%, and >10% for the primary outcome, the net absolute effect in a sample of 1000 patients is that the SAMPE model will result in an inappropriate estimate of 17 patients compared with risk estimation based on the new Ex-Care model. A *post-hoc* analysis of our sample size power was superior to 0.9 for all predictors (see Supplementary file S8 for details).

Temporal validation and comparison of Ex-Care performance with existing risk scores

A total of 1173 patients were included in the dataset used to compare the risk models. A total of 41 patients died after surgery (3.5%). Figure 2 illustrates the ROC curves for each model, and describes the comparison between the models according to the DeLong test. There was a significant difference between Ex-Care and RCRI (P<0.05), which had moderate performance. The CCI also had moderate performance (c-statistic 0.82; 95% CI, 0.77–0.90), without statistical significance compared with Ex-Care. The Ex-Care discrimination had high performance (c-statistic 0.90; 95% CI, 0.84–0.93) as well as the SORT model (c statistic 0.91; 95% CI, 0.89–0.95), and was as well calibrated (Hosmer–Lemeshow statistic 5.29; P=0.71) as the SORT model (Hosmer–Lemeshow statistic 5.36; P=0.61) (see Supplementary file S9 for calibration details).

Ex-Care prediction of morbidity risk

The presence of complications was evaluated with the POMS scale on postoperative days 3 and 7.[20] A total of 485 (40.4%) patients suffered at least one complication on day 3 and 208 (17.3%) did so on day 7. Supplementary file S10 shows the frequency of complications on the third postoperative day according to risk classes. The relative risk (RR) of complications according to Ex-Care model risk classes is presented on Table 4. The RR of any complication on the third postoperative day increased significantly in higher Ex-Care risk classes. Reliable confidence intervals related to the renal, infectious, and gastrointestinal domains of the POMS scale[20] confirmed the increased incidence of complications as risk class rose.

Model presentation and utilisation

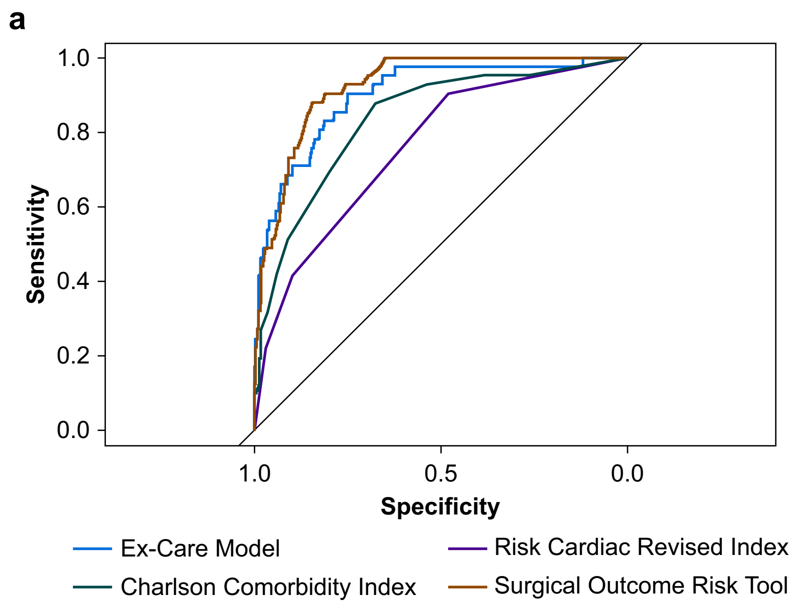
We developed the Ex-Care app-based approach that calculates the predicted probability of death for each possible combination of variables. This tool might overcome what would otherwise be a considerable challenge, performing a calculation based on a logistic regression equation at the patient's bedside before surgery. The calculator is available at https://play.google.com/store/apps/details?id=excare.model or https://apps.apple.com/br/app/excare/id1515296910?l=en. The risk classes are presented in different colours to facilitate the handover and postoperative assistance processes.

Discussion

Considering a trend for models with high numbers of risk factors, the Ex-Care model highlights the fact that few clinical and surgical variables (age, ASA physical status, surgical degree, and surgical nature) can predict, with high accuracy, postoperative morbidity and mortality. Temporal validation demonstrated that Ex-Care is more accurate than the RCRI score, and as good as the CCI and SORT models. Moreover, its predictor variables, routinely recorded and accessible before surgery, encompass a parsimonious model that has a clinically useful calibration for risk communication, and also excellent discrimination for triage.

Table 3 Prognostic capability of Ex-Care model in predicting postoperative death according to each risk class. CI, confidence interval.

Ex-Care risk class (predicted mortality)	Number of patients	Deaths (%)	Hazard ratio (95% CI)	P-value
Class I: <2%	12 810	53 (0.41)	Ref	
Class II: between 2% and 5%	2035	63 (3.09)	3.61 (2.5–5.23)	<0.01
Class III: between 5% and 10%	751	53 (7.05)	5.54 (3.76–8.19)	<0.01
Class IV: >10%	1022	296 (28.96)	21.78 (16.06–29.54)	<0.01



b

	AUROC (CI)	DeLong Test (Comparison with Ex-Care Model)
Ex-Care Model	0.90 (0.84 - 0.93)	–
Surgical Outcome Risk Tool	0.92 (0.89 - 0.95)	0.20
Risk Cardiac Revised Index	0.76 (0.67 - 0.72)	< 0.01
Charlson Comorbidity Index	0.82 (0.77 - 0.90)	0.06
ASA Physical Status	0.76 (0.71 - 0.91)	0.02

Fig 2. (a) ROC curves of the Ex-Care model, the Revised Cardiac Risk Index, and the Charlson comorbidity index for predicting postoperative in-hospital mortality. (b) Comparison of the AUROCs for the Ex-Care model, the Revised Cardiac Risk Index, and the Charlson Comorbidity Index, their respective CI, and De Long test significance. AUROC, area under the receiver operating characteristics; CI, confidence interval; ROC, receiver operating characteristics.

Advantages of the Ex-Care model

In an effort to optimise risk prediction, the Ex-Care model incorporates contemporary statistical evaluations and a simplified, plausible selection of variables that are intuitively linked to higher risk. The surgical severity with dichotomous division facilitated the comprehension of the final user because the division in several strata is not intuitive and is far from consensual between physicians, managers, and countries. Also, patient age, a variable that encompass the burden of physiologic reserve,[27,28] was validly modified to a non-linear, more realistic method using the splines approach, which enriched our result. In the Ex-Care model, individuals older than 70 yr had progressive, significant increase in the probability of death.

Our eventual model provided excellent performance, with an AUROC of 0.92. It is highly unlikely that a more complex model could meaningfully improve surgical risk assessment, as the performance of the model is excellent, in more than one large sample. The complete model equation is available in a mobile application, facilitating communication for all those planning and caring for surgical patients. Also, higher risk classes of the Ex-Care model were predictors for renal, infectious, and gastrointestinal complications on postoperative days 3 and 7.

Ex-Care model compared with other risk models

Traditional preoperative risk assessment tools such as the ASA-PS,[29] the RCRI score,[30] and the CCI,[31] although widely used worldwide for predicting postoperative mortality, have considerable limitations. Most do not consider the magnitude of patient age or type of surgery the patient will undergo. A systematic review[32] that included more than 790 000 patients showed that the general mortality prediction of the RCRI was poor (AUC=0.62; range, 0.54–0.78), a finding confirmed with a recent artificial intelligence assessment.[33] Nevertheless, it performed well in the setting for which it was originally designed: predicting postoperative cardiac complications.[34]

Table 4 Multivariate Poisson Regression of Ex-Care are risk classes and postoperative complications according to the POMS. CI, confidence interval; POMS, Postoperative Morbidity Survey.

	Relative risk of Ex-Care risk classes (CI)						
	Class I <2%	Class II 2–5%	P-value	Class III 2–5%	P-value	Class IV >10%	P-value
Complication on third postoperative day	ref	2.11 (1.70–2.62)	<0.01	3.46 (2.73–4.38)	<0.01	5.08 (4.15–6.22)	<0.01
Complication on seventh postoperative day	ref	3.20 (2.21–4.62)	<0.01	5.85 (3.71–9.25)	<0.01	9.68 (6.89–13.58)	<0.01
Unplanned intensive care admission	ref	9.56 (3.72–24.57)	<0.01	11.71 (3.88–35.39)	<0.01	24.84 (10.02–61.41)	<0.01
Morbidity according POMS domains on third postoperative day							
Cardiac	ref	1.025 (0.11–9.16)	0.25	5.85 (1.09–31.43)	<0.01	30.65 (10.29–91.23)	<0.01
Pulmonary	ref	7.17 (3.05–16.86)	<0.01	7.32 (2.46–21.80)	<0.01	26.27 (11.8–58.48)	<0.01
Renal	ref	2.60 (1.88–3.59)	<0.01	3.90 (2.61–5.82)	<0.01	4.19 (2.95–5.96)	<0.01
Neurological	ref	9.83 (3.46–27.92)	<0.01	11.71 (3.39–40.47)	<0.01	33.28 (12.42–89.12)	<0.01
Infectious	ref	1.72 (1.26–2.35)	<0.01	2.40 (1.63–3.55)	<0.01	3.68 (2.79–4.85)	<0.01
Haematological	ref	4.09 (0.82–20.36)	0.08	3.90 (0.40–37.55)	0.23	17.51 (4.38–70.03)	<0.01
Gastrointestinal	ref	1.91 (1.01–3.60)	0.04	3.51 (1.66–7.40)	<0.01	4.96 (2.73–8.99)	<0.01

The CCI[9] provided an accurate prediction of 30 day mortality, with similar performance to the Ex-Care model (c-statistic: 0.82 *vs* 0.90, respectively), but it does not consider the actual surgery to be undergone. Our model is based on a more contemporaneous approach such as those proposed by the authors of the SMP-M[13] and SORT[11] models, that consistently showed increased accuracy combining the patient health status and the severity of the procedure. The SORT model[11] developed in a UK population, comprises six variables: ASA-PS grade, urgency, surgical specialty, surgical severity, cancer, and age. We demonstrated that the performance of the Ex-Care model is at least comparable with the SORT model, to which it is similar but with fewer and simplified variables.

International context

Our model, as far as we know, is the first risk model for postoperative mortality prediction developed in Latin America. It proved simple and accurate, even with less variables than some recent models that have been validated in high-income countries (SORT,[11] NZRISK)[35] and in low-income countries (African Surgical Outcome Study [ASOS (African Surgical Outcomes Study)] risk calculator).[36] The ASOS model indicated that surgical aspects, such as type of surgery, are stronger risk factors than the clinical ones. Differences in available resources for surgical procedures in Africa might explain this result. This finding contrasts with the strength of the ASA-PS in our risk model, and, most probably, reflects one aspect of our National Health System, with the fragmentation of assistance and the prioritisation of primary care still in its embryonic stages, leading patients to be operated under worsened i conditions of their diseases.

Strengths and limitations

Ex-Care is a feasible risk model for middle-income countries built with a large heterogeneous cohort of adults undergoing noncardiac surgery. Its validation was accomplished with three classic stratification tools and its overall performance was evaluated with more than one measure (the c-statistic, Brier score, observed *vs* predicted deaths, and NRI). Finally, an app-based approach was designed to address the clinical needs. However, it has several limitations: (1) it was retrospective; (2) it was performed at a single medical centre; (3) it has, as its most significant predictor, the ASA physical status, which reflects patients' global health irrespective of the body systems[29,37]; and (4) the outcome in-hospital mortality is suboptimal, justified by the absence of an unified electronic records that could incorporate long-term mortality.

Clinical and future implications

High-risk patients can be accurately identified by the Ex-Care model, which requires only preoperative data variables. This finding could make this model an instrument for timely engagement between patient and caregivers for collaborative decision making, postoperative allocation, and processes changes. External validation of the Ex-Care model at other institutions is advisable for broad use. For this, we are working on a national model that encompasses different regions and health systems peculiarities considering the dimension of our continental country (CAAE 04448118.4. 1001.5327, under review number: BJAN-D-20-00116). There is also the need to identify whether its adoption improves the quality of care and the best allocation of resources in a health system where inequity needs to be fought. To target better care for high-risk patients, the Ex-Care Research Group is currently comparing the outcomes of 48 h postoperative co-managed care to usual postoperative ward care. (https://clinicaltrials.gov/ct2/show/NCT04187664).

Conclusions

The Ex-Care risk model proves very efficient at identifying high-risk patients before surgery, and at pinpointing those at risk as a result of severe postoperative complications. Although multicentre studies need to be done before its widespread adoption, Ex-Care provides a template for LMICs to generate local and pragmatic models. This should inform perioperative policies concerning surgical assessment and perioperative care pathways in an inequity-based environment where more accurate decisions need to be made and where the magnitude of postoperative mortality is still not given due importance. It is expected that these instruments could ground perioperative policies concerning surgical assessment and perioperative care pathways in an inequity based environment where more accurate decisions need to be made and where the magnitude of postoperative mortality is still not given due importance.

Authors' contributions

Conception and design of the study: CSG, SCP, WC, LCC
Data acquisition: CSG, SCP, LSMO, MLB, MBL
Data analysis and interpretation: CSG, SMJC, WC, LCC
Writing the first draft of the manuscript: CSG LCC
Manuscript revision: CSG, WC, LCC
Read and approved the final version of the manuscript: all authors

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Declarations of interest

The authors declare that they have no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bja.2020.09.036.

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