

UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL  
FACULDADE DE MEDICINA  
PROGRAMA DE PÓS-GRADUAÇÃO: CIÊNCIAS MÉDICAS

**DESENVOLVIMENTO E VALIDAÇÃO DE UM MODELO DE PREDIÇÃO DE  
PROBABILIDADE DE MORTE NO PÓS-OPERATÓRIO E O IMPACTO DE SUA  
INCORPORAÇÃO NA DETERIORAÇÃO CLÍNICA NO PÓS-OPERATÓRIO**

CLÁUDIA DE SOUZA GUTIERREZ

Porto Alegre  
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CLÁUDIA DE SOUZA GUTIERREZ

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Tese apresentada ao Programa de Pós-Graduação em Medicina: Ciências Médicas da Universidade Federal do Rio Grande do Sul como requisito parcial para a obtenção do título de Doutora em Medicina.

Porto Alegre

2019

## CIP - Catalogação na Publicação

Gutierrez, Cláudia de Souza  
Desenvolvimento e validação de um modelo de  
predição de probabilidade de morte no pós-operatório e  
o impacto de sua incorporação na deterioração clínica  
no pós-operatório / Cláudia de Souza Gutierrez. --  
2019.  
177 f.  
Orientador: Luciana Cadore Stefani.

Tese (Doutorado) -- Universidade Federal do Rio  
Grande do Sul, Faculdade de Medicina, Programa de  
Pós-Graduação em Medicina: Ciências Médicas, Porto  
Alegre, BR-RS, 2019.

1. Risco perioperatório. 2. Escores de risco. 3.  
Modelos prognósticos. 4. Mortalidade pós-operatória.  
5. Complicações pós-operatórias. I. Stefani, Luciana  
Cadore, orient. II. Título.

## **AGRADECIMENTOS**

À minha orientadora, Professora Luciana Cadore Stefani, que me inspira desde o início da formação como anestesista, através do seu profissionalismo e amor à arte de ensinar. O seu suporte e a sua dedicação tornaram possível um projeto que se estende para além da teoria e coloca o anestesista como agente transformador dos cuidados perioperatórios;

Aos professores do PPGCM da Faculdade de Medicina da UFRGS, pelo aprendizado ao longo destes quatro anos, fundamentais para a evolução desta tese. Ao professor Wolnei Caumo, pela competência na coordenação deste Programa de Pós-Graduação e pelo seu exemplo de excelência em pesquisa;

Às professoras Helena Arenson Pandikow e Elaine Felix, por terem vislumbrado um futuro além das fronteiras do centro cirúrgico e edificado, com coragem e determinação, o Serviço de Anestesia e Medicina Perioperatória do HCPA.

Aos meus colegas e residentes do Hospital de Clínicas de Porto Alegre, que participaram ativamente de todas as fases deste estudo e seguem dedicando-se diariamente com devoção aos cuidados da nossa população cirúrgica;

Ao Hospital de Clínicas de Porto Alegre e à Universidade Federal do Rio Grande do Sul, por incentivarem a excelência clínica e fornecerem os meios para o aperfeiçoamento contínuo;

À minha família, fonte de inspiração, afeto e segurança. O apoio incondicional e o suporte emocional ao longo do desenvolvimento deste projeto o tornaram possível.

## RESUMO

A estratificação do risco de morte e complicações no período perioperatório ainda é um desafio aos profissionais de diferentes áreas ligadas à assistência do paciente cirúrgico. Modelos prognósticos e escores de risco devem ser acurados na predição do desfecho, validados em diferentes populações, analisados quanto a sua calibração e periodicamente atualizados. Embora existam diferentes escores e modelos descritos na literatura, não há instrumento validado e de aplicabilidade clínica factível na população brasileira.

A presente tese teve como objetivo suprir essa lacuna na área da pesquisa voltada ao paciente cirúrgico e resultou na construção de um modelo de risco nacional, na sua subsequente validação e comparação com outros modelos existentes e na desafiadora implementação na prática clínica.

Para a construção do modelo inicial, utilizamos dados de mais de 13.000 pacientes cirúrgicos do Hospital de Clínicas de Porto Alegre (HCPA). Desenvolvemos o modelo baseados nas características de um instrumento de estratificação de risco ideal: composto por poucas variáveis preditoras, acurado em relação ao desfecho e de fácil aplicabilidade. O modelo resultante foi denominado modelo SAMPE, em alusão ao Serviço de Anestesia e Medicina Perioperatória do HCPA. As 4 variáveis selecionadas para compor o modelo (idade, classificação da *American Society of Anesthesiologists* – ASA, severidade e natureza da cirurgia) foram analisadas através de um modelo de regressão logística, cujo desfecho foi óbito na internação hospitalar em até 30 dias pós-operatórios. A acurácia do modelo SAMPE foi avaliada através da estatística C, apresentando uma excelente capacidade discriminativa conforme a área sob a curva ROC (AUROC). Utilizando o valor de corte de 0.02 de probabilidade predita de morte em até 30 dias, quatro classes de risco foram criadas para facilitar o uso do modelo: Classe I ( $< 2\%$ ), Classe II ( $\geq 2\% \text{ e } < 5\%$ ), Classe III ( $\geq 5\% \text{ e } < 10\%$ ) e Classe IV ( $\geq 10\%$ ).

Posteriormente, comparamos a acurácia do modelo SAMPE com o Índice de Risco Cardíaco Revisado (IRCR) e do Índice de Comorbidades de Charlson (ICC), que são instrumentos validados e tradicionalmente utilizados. O modelo SAMPE demonstrou superioridade discriminativa, com os seguintes resultados: AUROC<sub>SAMPE</sub> = 0.907, AUROC<sub>IRCR</sub> = 0.767 e AUROC<sub>ICC</sub> = 0.822.

De posse de um modelo validado e considerado robusto, propôs-se a sua aplicabilidade na assistência. Para facilitar a utilização prática do modelo pelos anestesiologistas do HCPA, desenvolvemos uma ferramenta *web-based* compartilhada na plataforma Google. A incorporação do modelo foi inicialmente realizada no pós-operatório imediato, na Sala de Recuperação Pós-Anestésica (SRPA). Os pacientes foram categorizados quanto ao seu risco e sinalizados por cores, sendo que aqueles de alto risco (probabilidade de morte  $> 5\%$ ) receberam uma otimização dos processos de alta pela equipe médica e de transferência de cuidado pela enfermagem da SRPA (*handover*) para a unidade de internação.

A avaliação do impacto da incorporação do modelo SAMPE na rotina assistencial foi feita através da análise das chamadas do Time de Resposta Rápida (TRR) no pós-operatório, em um estudo antes e depois (*before-after study*). Não houve uma diferença significativa na incidência total de chamadas do TRR, mas observamos uma redução do número de chamadas na Classe de risco IV (muito alto risco) e um aumento na Classe de risco II (risco intermediário), após a implementação do modelo na prática clínica. Não obstante, o modelo SAMPE foi

amplamente aceito pelas equipes assistenciais, possibilitando o desenvolvimento de novos projetos institucionais que incorporam otimização de cuidados por 48 horas ao grupo de alto risco.

Por fim, reanalisamos as variáveis do modelo, refinando a idade através de uma técnica estatística conhecida como *splines*, além de simplificarmos a classificação de risco das cirurgias. Esse ajuste de variáveis, utilizando dados de uma amostra contemporânea de 16.618 pacientes, gerou um novo modelo, que chamamos de SAMPE II. Novas medidas de *performance* geral, acurácia, calibração e índice de reclassificação foram realizadas, indicando excelente discriminação.

O modelo SAMPE apresenta-se como uma alternativa promissora em termos de estratificação de risco cirúrgico no Brasil. O modelo é simples, acessível, acurado e validado em diferentes tipos de cirurgia, com acurácia superior a escores de risco tradicionais e validados internacionalmente. A aceitação e a utilização na prática assistencial permitiu a identificação objetiva dos pacientes de alto risco, colaborando para a idealização de linhas de cuidado compatíveis, facilitando a comunicação entre as equipes e os processos de transferência de cuidados. A maior contribuição da presente tese encontra-se na possibilidade de otimização do trajeto do paciente de alto risco no Brasil. A ampla validação dos modelos criados em outros centros do país, assim como a amplificação do cuidado do paciente de alto risco no pós-operatório, são projetos frutos da linha de pesquisa aqui descrita e iniciada.

**Palavras-chave:** Risco perioperatório. Escores de risco. Modelos prognósticos. Mortalidade pós-operatória. Complicações pós-operatórias.

## ABSTRACT

Death risk stratification and complications in the perioperative period are still a challenge for professionals in different areas related to surgical patient care. Prognostic models and risk scores should ideally be accurate in outcome prediction, validated in different populations, analyzed in terms of their calibration, and periodically updated. Although a number of scores and models have been described in the literature, there are no validated instruments with viable clinical applicability to the Brazilian population.

The present thesis aimed to fill this gap in the research area focused on surgical patient and resulted in the construction of a national risk model, its subsequent validation and comparison with other existing models and its challenging implementation in clinical practice.

For the construction of the initial model, we used data from more than 13,000 surgical patients at the Hospital de Clínicas de Porto Alegre (HCPA). We developed the model based on the characteristics of an ideal risk stratification instrument: composed of few predictor variables, accurate in relation to the outcome and easily applicable. The resulting model was named SAMPE model, alluding to the Anesthesia and Perioperative Medicine Service. The 4 variables selected to compose the model (age, American Society of Anesthesiologists (ASA) classification, severity and nature of the surgery) were analyzed using a logistic regression model, in which the outcome was in-hospital death within 30 postoperative days. The accuracy of the SAMPE model was evaluated using the C statistic, presenting an excellent discriminative capacity according to the area under the ROC curve (AUROC). Using the cut-off value of 0.02 predicted probability of death within 30 days, four risk classes were created to facilitate the use of the model: Class I (<2%), Class II ( $\geq 2\%$  and <5%), Class III ( $\geq 5\%$  and <10%) and Class IV ( $\geq 10\%$ ).

Subsequently, we compared the accuracy of the SAMPE model with the Revised Cardiac Risk Index (IRCR) and the Charlson Comorbidity Index (ICC), which are validated and traditionally used instruments. The SAMPE model demonstrated discriminative superiority, with the following results: AUROC<sub>SAMPE</sub> = 0.907, AUROC<sub>IRCR</sub> = 0.767 and AUROC<sub>ICC</sub> = 0.822.

Having a validated and robust model, we proposed its use in clinical practice. To facilitate the practical use of the model by HCPA anesthetists, we developed a web-based tool shared on the Google platform. The incorporation of the model was initially performed in the immediate postoperative period, in the Post Anesthetic Recovery Room (PACU). Patients were categorized by risk and color-coded, and those at high risk (probability of death > 5%) had their discharge and handover processes from PACU to the inpatient unit optimized. The evaluation of the impact of the incorporation of the SAMPE model in the care routine was made through the analysis of the postoperative Rapid Response Team (RRT) calls in a before-after study. There was no significant difference in the total incidence of RRT calls, but we observed a reduction in the number of calls in Class IV (very high risk) and an increase in Class II (intermediate risk) after the implementation of the model. Nevertheless, the SAMPE model was widely accepted by the health care providers, enabling the development of new institutional projects that incorporate 48-hour care optimization into the high-risk group. Finally, we reanalyzed the model variables, refining the variable age through a statistical technique known as splines, and simplifying the risk classification of the surgeries. This adjustment of variables, using data from a contemporary sample of 16.618 patients, generated a new model, which

we call SAMPE II. New measures of overall performance, accuracy, calibration and reclassification index were performed, indicating excellent discrimination.

The SAMPE model presents itself as a promising alternative in terms of surgical risk stratification in Brazil. The model is simple, accessible, accurate and validated in different types of surgery, with accuracy higher than traditional and internationally validated risk scores. The acceptance and use in clinical practice allowed the objective identification of high-risk patients, contributing to the design of compatible care pathways, facilitating communication between health providers and handover process. The major contribution of the present thesis is the possibility of optimizing the perioperative pathway of high-risk surgical patients in Brazil. The wide validation of the models created in other centers of the country, as well as the amplification of postoperative high-risk patient care, are projects that are the result of the research described and initiated here.

**Keywords:** Perioperative risk. Risk scores. Prognostic models. Postoperative mortality. Postoperative complications.

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## LISTA DE ABREVIATURAS E SIGLAS

ACD	Análise da Curva de Decisão
ACSNSQIP	<i>American College of Surgeons national Surgical Quality Improvement Program</i>
AMB	Associação Médica Brasileira
APACHE	<i>Acute Physiology and Chronic Health Evaluation</i>
ASA-PS	<i>American Society of Anesthesiologists Physical Status Classification System</i>
AUC	<i>Area under the ROC Curve</i>
AUROC	<i>Area Under de Receiver Operating Characteristic curve</i>
BUPA	<i>British United Provident Association</i>
CEDOP	<i>Confidential Enquiry into Perioperative Deaths</i>
EUSOS	<i>European Outcome Study</i>
FTR	<i>Failure to Rescue</i>
HCPA	Hospital de Clínicas de Porto Alegre
ICC	Índice de Comorbidades de Charlson
IRCR	Índice de Risco Cardíaco Revisado
mE-PASS	<i>Modified Estimation of Physiologic Ability and Surgical Stress</i>
MICA	<i>Myocardial Infarction / Cardiac Arrest</i>
NB	<i>Net Benefit</i>
NELA	<i>National Emergency Laparotomy Audit</i>
NHS	<i>National Health Service</i>
NRI	<i>Net Classification Improvement</i>
NSQIP	<i>National Surgical Quality Improvement Program</i>
NTDB	<i>National Trauma Databank</i>
PACU	<i>Post-Anesthetic Care Unit</i>
POMS	<i>Postoperative Morbidity Survey</i>
POSSUM	<i>Physiological and Operative Severity Score for the Enumeration of Mortality and Morbidity</i>
ROC	<i>Receiver Operating Characteristic</i>
SAMPE	Serviço de Anestesia e Medicina Perioperatória
SMP-M	<i>Surgical Mortality Probability Model</i>

SORT	<i>Surgical Outcome Risk Tool</i>
SRPA	Sala de Recuperação Pós-Anestésica
SUS	Sistema Único de Saúde
TRIPOD	<i>Transparent Reporting of Multivariable Prediction Model for Individual Statement Prognosis or Diagnosis</i>
TRR	Time de Resposta Rápida
UTI	Unidade de Terapia Intensiva

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## 1 INTRODUÇÃO

A cirurgia pode ser considerada uma jornada que o paciente enfrenta em diferentes momentos, com distintos propósitos, ao longo de sua vida. As consequências do ato cirúrgico podem variar e complicações são bastante frequentes. Embora avanços substanciais tenham sido alcançados em relação à segurança na área da anestesia nos últimos 50 anos, não houve melhora em grau similar nos desfechos perioperatórios. Complicações relacionadas à lesão aguda de diferentes órgãos, que levam à falência de um ou vários sistemas, constituem o principal precursor da morte após a cirurgia. A mortalidade hospitalar no cenário de doença crítica pós-operatória pode chegar a 20,6%, constituindo, portanto, problema de saúde pública<sup>1</sup>.

Entendemos, portanto, que o desenvolvimento de desfechos adversos após a cirurgia ocorre pela interação entre a resposta ao trauma, as reservas fisiológicas para lidar com esse trauma e a magnitude da cirurgia<sup>2</sup>. Nessa perspectiva, a resposta à cirurgia se torna o insulto patológico e a consequente disfunção orgânica associada se converte na condição que deve ser o foco do cuidado no pós-operatório. O objetivo da medicina perioperatória é fornecer o melhor cuidado pré, intra e pós-operatório, o que é possível apenas com assistência médica multidisciplinar e integrada aos pacientes, desde a sua indicação cirúrgica até a recuperação completa<sup>3</sup>. Entretanto, a fim de alcançarmos essa assistência integral, é necessário construirmos linhas assistenciais específicas para o paciente cirúrgico ou refinarmos os caminhos já existentes.

Esta é justamente a ideia atual da medicina perioperatória: transformar o conceito restrito de buscar os melhores desfechos individuais no pós-operatório imediato em uma proposta mais ampla, que visa contribuir para a saúde global da população e a sustentabilidade do sistema de saúde com um todo<sup>4</sup>. Isso pode ser atingido com intervenções prévias à cirurgia, incluindo tomada de decisão compartilhada, gestão de comorbidades e mudança comportamental colaborativa. Intervenções individualizadas, adaptadas ao risco, podem direcionar os cuidados intra e pós-operatórios particularmente otimizando as transferências de cuidado e os esforços no sentido de prevenir a morte como consequência de complicações no pós-operatório (*failure to rescue*)<sup>5</sup>.

A estimativa do risco de eventos adversos perioperatórios pode auxiliar nas

decisões de manejo do paciente, na elaboração do consentimento informado, no planejamento e na escolha de monitorização transoperatória, bem como na adequada alocação pós-operatória<sup>6</sup>. Sabemos que um pequeno grupo de pacientes considerado de alto risco é o responsável pelo maior número de mortes no pós-operatório, o que torna essa identificação de extrema importância<sup>7</sup>. Porém, tal medida constitui-se desafio, pois, embora os processos médicos de tomada de decisão sejam fundamentados na lógica e probabilidade, as evidências indicam que outros fatores difíceis de mensurar, como preferências individuais, preconceitos cognitivos, emoções e experiências anteriores, desempenham um papel relevante em vários níveis da árvore de decisão<sup>8</sup>. Portanto, é desejável incluir ferramentas consistentes e estatisticamente orientadas no processo de tomada de decisão, a fim de melhorar a precisão do julgamento e embasar ações que aumentam a segurança do paciente.

A ferramenta de estratificação de risco ideal deve ser simples, com poucas variáveis de fácil acesso, acuradas na predição do desfecho e factíveis para uso prático<sup>9</sup>. Além da avaliação da capacidade discriminativa e da calibração, essa ferramenta idealmente deve ser validada em diferentes contextos (capacidade de generalização) e avaliada quanto ao impacto clínico<sup>10,11,12</sup>. Existem inúmeros escores e modelos preditivos de risco descritos na literatura, desde os mais simples com poucas variáveis, como o ICR, até modelos complexos, como o *American College of Surgeons National Surgical Quality Improvement Program (ACSNSQIP Surgical Risk Calculator)*. A extrapolação direta de modelos usados em países desenvolvidos pode não refletir o verdadeiro cenário de nossa população, contexto no qual variáveis relacionadas ao acesso aos serviços de saúde e à eficiência desses serviços desempenham um importante papel.

Sendo assim, esta tese visa preencher a lacuna da ausência de modelos de risco nacionais que reflitam a população de pacientes atendidos pelo Sistema Único de Saúde (SUS). Modelos esses que possam ser usados como base de programas destinados à melhoria dos processos relativos ao atendimento do paciente cirúrgico, desde a decisão de operar até a reabilitação a longo prazo. A pesquisa, pois, alicerçou-se na construção e validação de um modelo de estratificação de risco cirúrgico, utilizando dados da população cirúrgica do Hospital de Clínicas de Porto Alegre. A posterior incorporação do referido modelo voltado à assistência no trans e pós-operatório imediato deu origem aos seguintes artigos:

Artigo 1: Derivation and validation of a preoperative risk model for postoperative mortality (SAMPE model): An approach to care stratification.

Neste estudo, descrevemos a construção e validação do modelo de risco (Modelo SAMPE) que incorpora dados do paciente e da cirurgia, fornecendo de forma acurada a probabilidade de morte intra-hospitalar em até 30 dias.

Artigo 2: The Accuracy of the SAMPE risk model for postoperative in-hospital mortality prediction compared to the Revised Cardiac Risk and Charlson Comorbidity Indexes

Nesta produção, comparamos a acurácia do Modelo SAMPE com dois escores amplamente utilizados, o IRCR e o ICC, identificando sua relação com complicações no pós-operatório pela ocorrência de morbidade de acordo com o questionário POMS.

Artigo 3: Effectiveness of PACU postoperative pathway triggered by a new preoperative stratification tool (SAMPE Model): impact on postoperative deterioration.

Neste artigo, descrevemos a incorporação da estratificação de risco na prática assistencial, as modificações de processos na SRPA e o impacto na deterioração pós-operatória, comparando as proporções de chamadas do TRR antes e depois da implantação do modelo.

Artigo 4: The high-risk surgical patient highlighted: validation of a lean and accurate predictive model of postoperative death in a cohort of 16662 patients: The SAMPE II model

Neste estudo, descrevemos o refinamento e a validação do Modelo SAMPE em uma amostra contemporânea de pacientes cirúrgicos, aferindo a capacidade discriminativa, calibração e o índice de reclassificação desse modelo, o que configura um novo: o Modelo SAMPE II.

## 2 REVISÃO DE LITERATURA

### 2.1 ESTRATÉGIA DE BUSCA BIBLIOGRÁFICA

Quanto à revisão de literatura, identificamos artigos publicados nos últimos dez anos que abordam os principais fatores de risco para morbi-mortalidade perioperatória, os modelos preditivos de risco usados atualmente e as complicações mais frequentemente associadas ao ato anestésico-cirúrgico. Utilizamos as bases de dados PubMed e Embase. Além dos artigos recuperados na pesquisa em base de dados, averiguamos aqueles provenientes de referências cruzadas e anteriores à data de busca devido a sua relevância clínica e importância histórica. Pesquisamos as palavras-chave no Título e Resumo, com os *MeSH terms* e *Emtree terms* correspondentes. Os *MeSH terms* pesquisados na base de dados PubMed foram: *perioperative care, risk adjustment, risk assessment, failure to rescue, hospital rapid response team, postoperative complication, hospital mortality*. Os *Emtree terms* pesquisados na base de dados Embase foram: *perioperative period, risk assessment, failure to rescue, rapid response team, postoperative complication, surgical mortality, surgical morbidity*. Os resultados da busca bibliográfica encontram-se sumarizados na tabela 1.

#### Palavras-Chave:

1. *Perioperative risk;*
2. *Risk models;*
3. *Revised Cardiac Risk Index;*
4. *Charlson Comorbidity Index;*
5. *Failure to Rescue;*
6. *Rapid Response Team;*
7. *Postoperative outcomes;*
8. *Surgical mortality and morbidity.*

**Tabela 1** - Resultados da busca bibliográfica

Palavra-chave	PUBMED	UTILIZADO	EMBASE
1	832	9	365
2	69	4	46
3	42	6	112
3 + 1	12	1	9
3 + 7	28	5	4
4 + 1	133	3	196
4 + 7	10	1	70
5 + 1	451	5	67
5 + 2	102	2	93
6 + 1	28	1	11
6 + 7 + 8	354	6	415
Total	2.061	43	1.390

**Fonte:** Elaborado pela autora.

## 2.2 RISCO CIRÚRGICO – PERSPECTIVAS ATUAIS

Estima-se que mais de 300 milhões de cirurgias ocorram no mundo a cada ano. Serviços de Cirurgia são parte fundamental de um Serviço Nacional de Saúde, estando presentes em países desenvolvidos e em desenvolvimento. A heterogeneidade de cenários manifesta-se nas diferentes taxas de mortalidade e complicações entre os países<sup>13,14</sup>. Embora comparações de taxas de morbimortalidade sejam difíceis de executar em função justamente dessa diversidade, acredita-se que em países desenvolvidos complicações maiores ocorram em 3 a 16% dos casos, com mortalidade de 0.4% a 0.8%. Já em países em desenvolvimento, a mortalidade após uma cirurgia pode chegar a 10%<sup>13</sup>. Esses números podem ser ainda maiores, visto que o acesso e registro de informações fidedignas referentes a complicações e óbito no pós-operatório são negligenciadas em alguns países.

Em uma coorte de 46.589 pacientes cirúrgicos de 28 países da Europa, a mortalidade geral foi de 4%, valor acima do esperado pelos autores. Apenas 8% desses pacientes foram admitidos em Unidades de Tratamento Intensivo, com permanência média de até dois dias. Dos pacientes que foram a óbito, 73% não foram admitidos na UTI em nenhum momento depois da cirurgia. Mesmo após

ajuste de variáveis confundidoras, uma grande variação das taxas de mortalidade foi observada entre os países, sugerindo a importância das diferenças demográficas, socioeconômicas e nas políticas de saúde<sup>15</sup>.

Acredita-se que em torno de 12% dos pacientes são considerados de alto risco cirúrgico, contribuindo com aproximadamente 80% das mortes pós-operatórias<sup>16</sup>. Diante de tal evidência, a identificação desse subgrupo é de suma importância. Entretanto, a correta estratificação de risco pode ser um desafio, apesar da existência de várias ferramentas disponíveis atualmente. Alguns fatores que contribuem para a baixa adesão são incertezas em relação à acurácia e validade externa, complexidade das ferramentas e das variáveis preditoras, à variabilidade de desfechos preditos e ausência de evidências quanto ao impacto da utilização prática.

## 2.3 DEFINIÇÃO DE VARIÁVEIS INDICATIVAS DE RISCO CIRÚRGICO

Inúmeros estudos recentes buscam identificar quais são os pacientes com maior risco no perioperatório. O *Royal College of Surgeons of England Working Group* define como paciente de alto risco aquele com mortalidade estimada > 5%, e de altíssimo risco quando a mortalidade estimada é >10%. A falta de consenso em relação à severidade das complicações cirúrgicas e as dificuldades em implementar escalas padronizadas para medir os desfechos dificultam as comparações entre diferentes ferramentas preditoras de risco<sup>17</sup>.

O instrumento de estratificação de risco ideal deve ser simples, acurado na predição do desfecho, incluindo poucas variáveis centradas no paciente e na cirurgia. Esse instrumento deve ser reproduzível e aplicável em diferentes cenários, além de ser acessível ao usuário<sup>17,9</sup>. A seguir, são descritas as variáveis mais comumente incorporadas aos modelos de risco perioperatório.

### 2.3.1 Variáveis Relacionadas ao Paciente

- ◆ IDADE

Não existe uma definição precisa ou qualquer marcador clínico a elucidar quem é "idoso" ou o que significa "idade avançada". O envelhecimento não é um processo abrupto, mas representa um contínuo no qual a população de idade

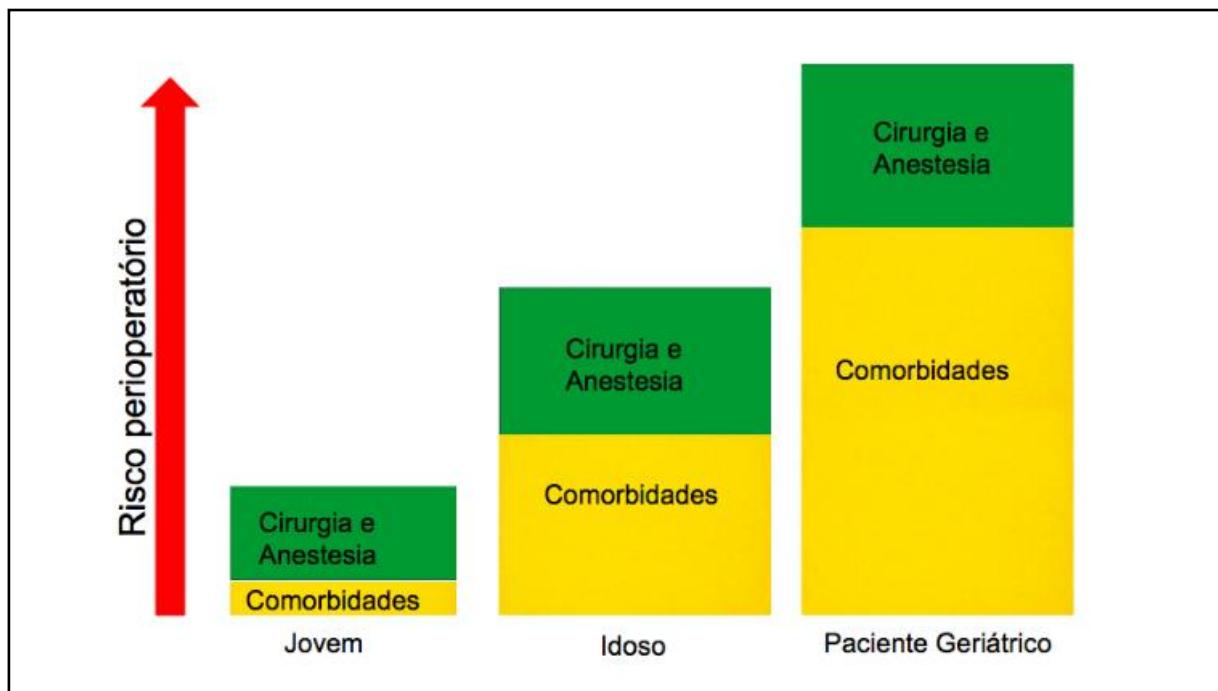
avançada é considerada um grupo extremamente heterogêneo<sup>18</sup>. Estima-se que a maioria das pessoas nascidas em países desenvolvidos durante o século 21 irá viver pelo menos até o seu centésimo aniversário. Tanto o crescimento do número de idosos quanto a complexidade inerente aos seus cuidados causam um aumento na demanda dos sistemas de saúde. O rápido crescimento da população idosa traz à tona a necessidade de uma melhor compreensão das exigências clínicas e da evolução natural desses pacientes que se submetem a qualquer tipo de cirurgia<sup>19</sup>.

Atualmente, cerca da metade de todas as operações nos Estados Unidos são realizadas em pessoas com mais de 65 anos de idade. Essa população de pacientes é de alto risco para morbidade e mortalidade, o que, consequentemente, aumenta também os custos hospitalares. A incidência de complicações eleva em até 26% a mortalidade pós-operatória em pacientes com mais de 80 anos<sup>20</sup>. Entre o já crescente grupo populacional cirúrgico de pacientes com 65 anos ou mais, o subgrupo de crescimento mais rápido é o dos maiores de 85 anos. Por conseguinte, um maior número de indivíduos apresentam-se para cirurgia com condições clínicas relacionadas à sua idade avançada, expostos a maior risco de complicações diante de um evento adverso. Portanto, não são surpreendentes os resultados que mostram idosos com a maior taxa de mortalidade na população cirúrgica adulta, sendo a média geral de aproximadamente 1,02%. Nos pacientes com idade entre 60 e 69 anos, a mortalidade é de 2,2%; nos de 70-79 anos, é de 2,9%; nos acima de 80 anos, é de cerca de 5,8 a 6,2%; e, naqueles com mais de 90 anos, é de 8,4%<sup>21</sup>.

Independente do escore ou modelo utilizado, os idosos invariavelmente possuem pontuação alta em termos de risco estimado de morte, tanto por causa da idade como pelas comorbidades. Os fatores que mais contribuem para o aumento do risco perioperatório relacionado à idade avançada são a diminuição da capacidade de reserva de órgãos para compensar as crescentes demandas fisiológicas necessárias durante a agressão cirúrgica e a progressiva manifestação de doenças crônicas<sup>22</sup>. Não apenas a idade cronológica parece influenciar, mas a presença de comorbidades, as incapacidades e a fragilidade que se inter-relacionam parecem contribuir para o aumento de risco. A desregulação dos sistemas imune, endócrino e hormonal, associado a um *up-regulation* de citocinas inflamatórias, leva a um estado de catabolismo, sarcopenia e disfunções subclínicas. Esse conjunto de alterações aumenta a vulnerabilidade do paciente aos estressores, sendo característico do fenótipo de fragilidade. Escores para avaliar a fragilidade (*Frailty*)

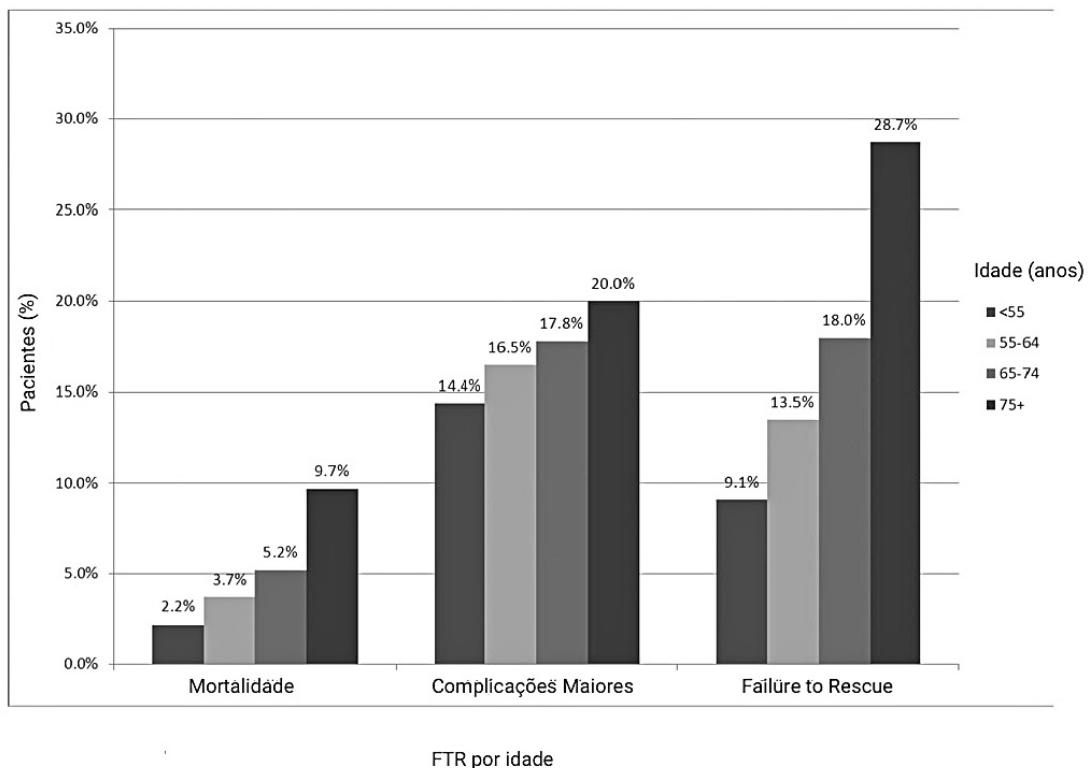
vêm sendo objetos de estudo na avaliação do risco perioperatório na população idosa<sup>23</sup>.

A figura 1 mostra o aumento do risco perioperatório com o aumento da idade e o peso que as comorbidades exercem sobre os desfechos, especialmente nos pacientes considerados geriátricos (idosos com múltiplas comorbidades).



**Figura 1** - Risco Perioperatório e Idade: aumento de risco relacionado à cirurgia/anestesia versus comorbidades em pacientes jovens, idosos saudáveis (idosos em processo de envelhecimento natural, sem comorbidades significativas) e “geriátricos” (idosos com diversas e significantes comorbidades). **Fonte:** Modificado de Boddaert et al., 2014<sup>24</sup>.

Além de uma maior taxa de mortalidade pós-operatória, a população idosa também apresenta maiores taxas de *failure to rescue* – morte precedida por uma complicaçāo pós-operatoria (figura 2) –, quadro esse que pode ser atribuído a uma menor reserva fisiológica e capacidade de resposta ao *stress*<sup>25</sup>.



**Figura 2 - Taxas de mortalidade, complicações maiores e FTR em diferentes grupos etários.**  
Fonte: Modificado de Ghaferi et al., 2016<sup>25</sup>.

#### ♦ COMORBIDADES

As comorbidades influenciam diretamente os desfechos pós-cirúrgicos. Em recente levantamento das causas dos óbitos em 11.562 procedimentos realizados no Hospital de Clínicas de Porto Alegre, evidenciamos mortalidade de 2,11% em pacientes internados até 30 dias. A análise qualitativa identificou que 50,7% desses óbitos foram considerados inevitáveis, sendo atribuídos às condições da doença de base<sup>26</sup>. A classificação *American Society of Anesthesiologists-Physical Status* (ASA-PS), apesar de originalmente ter sido criada para designar o estado basal de saúde pré-operatório, vem sendo rotineiramente utilizada na prática clínica a fim de avaliar o risco cirúrgico.

Introduzida em 1941 em artigo publicado por Saklad, a classificação referida tinha como objetivo estandardizar a avaliação do *status* funcional dos pacientes<sup>27</sup>. A facilidade de uso da ASA-PS faz com que seja amplamente aceita, porque, apesar da sua subjetividade, apresenta moderada variabilidade entre avaliadores conforme o estudo de Sankar e colaboradores<sup>28</sup>. Ela demonstra a vantagem de ser simples, de fácil aplicação, sendo amplamente conhecida, correlacionando-se positivamente

com a probabilidade de óbito e complicações no período pós-operatório em diversos estudos<sup>29,30,31</sup>. Essa escala compõe como variável clínica alguns escores e modelos de risco operatório, sendo utilizada como uma das principais variáveis de um modelo de risco desenvolvido através da análise de 298,772 pacientes submetidos à cirurgia não cardíaca, usando dados do *American College of Surgeons National Surgical Quality Improvement Program* (ACSNSQIP). Esse modelo apresentou alta acurácia na predição de morte em até 30 dias no pós-operatório (C statistic, 0.897)<sup>32</sup>.

No entanto, a escala da ASA é subjetiva, não fornecendo informações do procedimento cirúrgico, tampouco da probabilidade ou do risco de morte e de complicações, apresentando baixa acurácia quando utilizada isoladamente conforme verificado em alguns estudos<sup>9,33</sup>. A fim de reduzir essa subjetividade, recomendamos o uso de uma atualização recentemente publicada pela Sociedade Americana de Anestesia, disponível em: (<http://www.asahq.org/resources/clinical-information/asa-physical-status-classification-system>).

**Quadro 1 - ASA-PS: definição atual (sem mudança) e exemplos (novo)**

(continua)

Classificação ASA-PS	Definição	Exemplos, incluindo, mas não limitado a:
ASA I	Paciente normal e saudável	Saudável, não fumante, sem ou mínimo uso de bebida alcoólica
ASA II	Paciente com doença sistêmica leve	Doenças leves sem limitações funcionais importantes. Exemplos: fumante ativo, consumo social de álcool, gravidez, obesidade (30 <IMC <40), DM / HAS bem controlada, doença pulmonar leve
ASA III	Paciente com doença sistêmica grave	Limitações funcionais importantes. Uma ou mais doenças moderadas a graves. Exemplos incluem (mas não limitado a): DM ou HAS mal controlada, DPOC, obesidade mórbida (IMC ≥ 40), hepatite ativa, dependência ou abuso de álcool, marca-passo implantado, redução moderada da fração de ejeção, IRC submetida à diálise regular, bebê prematuro IPC <60 semanas, história (> 3 meses) de IAM, AVC, AIT ou CI / stents

**Quadro 1 - ASA-PS: definição atual (sem mudança) e exemplos (novo)**

(conclusão)

Classificação ASA-PS	Definição	Exemplos, incluindo, mas não limitado a:
ASA IV	Paciente com doença sistêmica grave, implicando ameaça constante à vida	Exemplos incluem (mas não limitado a): recente (<3 meses) IAM, AVC, AIT ou CI / stents, isquemia cardíaca contínua ou disfunção valvular grave, redução severa da fração de ejeção, sepse, CIVD, SARA ou IRC não submetida à diálise regular
ASA V	Paciente moribundo cuja expectativa de sobrevivência depende de operação.	Exemplos incluem (mas não limitado a): aneurisma abdominal / torácico rompido, trauma grave, sangramento intracraniano com efeito de massa, intestino isquêmico em face de patologia cardíaca significativa ou disfunção de múltiplos órgãos / sistemas
ASA VI	Paciente com morte cerebral declarada cujos órgãos estão sendo removidos para doação	

A adição do "E" indica cirurgia de emergência, existente quando o atraso no tratamento do paciente pode levar a um aumento significativo da ameaça à vida ou parte do corpo).

IMC: índice de massa corporal

DM: diabetes *mellitus*

HAS: hipertensão arterial sistêmica

DPOC: doença pulmonar obstrutiva crônica

IRC: insuficiência renal crônica

IPC: idade pós-concepção

IAM: infarto agudo do miocárdio

AVC: acidente vascular cerebral

AIT: ataque isquêmico transitório

CI: cardiopatia isquêmica

CIVD: coagulação intravascular disseminada

SARA: síndrome da angústia respiratória aguda

Aprovado pela Câmara de Delegados da ASA em 15 de outubro de 2014.

**Fonte:** American Society of Anesthesiologists

### **2.3.2 Variáveis Relacionadas à Cirurgia**

- ♦ NATUREZA DA CIRURGIA: ELETIVA VERSUS URGENTE

Enquanto o cuidado cirúrgico eletivo proporciona o benefício de uma avaliação abrangente e da otimização pré-operatória das situações de risco, a cirurgia de emergência impõe tempo limitado para a realização de ações essenciais ao cuidado. O estado de saúde basal e as comorbidades preexistentes dos pacientes que se apresentam com emergências cirúrgicas são muitas vezes desconhecidos. A ausência dessas informações e a escassez de tempo para otimização clínica devido ao caráter de urgência exacerbam a vulnerabilidade dos pacientes. A cirurgia de alto risco e a de emergência correlacionam-se positivamente em relação a uma maior mortalidade pós-operatória<sup>3,34,35</sup>.

Um estudo de coorte dinamarquês com 2889 pacientes submetidos à colectomia total demonstrou taxa de mortalidade de 1,0% em colectomias eletivas e de 5,3% nas de urgência<sup>36</sup>. Quanto aos pacientes com 60 anos ou mais, a mortalidade aumentou para 3,3% nos submetidos à colectomia eletiva e para 18,4% nos expostos ao procedimento em caráter de emergência.

Mallol e colaboradores conduziram um estudo observacional ao longo de dois anos na UTI cirúrgica de um hospital terciário espanhol cujos pacientes foram admitidos após a realização de cirurgia oncológica abdominal. Nos 112 pacientes submetidos à cirurgia de emergência, a mortalidade foi de 32,5% para a cirurgia de ressecção de urgência e de 42% para a paliativa urgente. Nos 787 pacientes que se submeteram à cirurgia programada, a mortalidade foi de 4,7% para os procedimentos de ressecção e de 12% para os paliativos<sup>37</sup>.

Uma coorte retrospectiva americana multicêntrica, utilizando-se dos bancos de dados do *National Trauma Data Bank* (NTDB) e do *American College of Surgeons National Surgical Quality Improvement Program* (ACSNSQIP) focou-se nos desfechos hospitalares em pacientes de trauma e cirurgia geral. Observou-se que pacientes de cirurgia geral de emergência tendiam a um *status* funcional inferior e um maior número de comorbidades quando comparados à pacientes de cirurgia geral eletiva. A mortalidade observada foi de 7,5% ( $n = 2.455$ ) em pacientes de trauma, 6,6% ( $n = 944$ ) nos de cirurgia geral de emergência e 1,4% ( $n = 1.631$ ) nos

de cirurgia geral eletiva<sup>38</sup>.

O caráter de urgência também é um fator de risco para complicações maiores, como parada cardiorrespiratória. Estudo realizado em um hospital geral terciário brasileiro entre 1996 e 2005, envolvendo 53.718 procedimentos anestésicos, avaliou prospectivamente a ocorrência de parada cardiorrespiratória durante a cirurgia ou na Sala de Recuperação. Nos 186 casos identificados, o *status* físico ASA ≥ 3, extremos de idade e cirurgia de emergência foram fatores de risco maiores para a ocorrência do desfecho<sup>39</sup>.

Em uma análise de 187 pacientes consecutivos submetidos a cirurgias de urgência no HCPA, observamos alta mortalidade em até 30 dias (14,4%), sendo o procedimento mais associado a laparotomia exploradora (47,7% de óbitos), índices esses elevados comparados com estatísticas globais<sup>40</sup>. Linhas de assistência à laparotomia estão sendo desenvolvidas no Reino Unido em um projeto nacional denominado *National Emergency Laparotomy Audit* (NELA). Tal projeto é constituído de uma série de medidas pré, intra e pós-operatórias para melhoria dos desfechos na população com múltiplas comorbidades submetida a cirurgias em condições não eletivas. Dentre as medidas pré-operatórias destacam-se o plano de cuidados pelo cirurgião, a brevidade na definição diagnóstica, o acesso formal ao risco de morte e complicações, a precoce administração de antibióticos e realização da cirurgia<sup>41</sup>.

#### ♦ PORTE DA CIRURGIA

O impacto do porte da cirurgia na morbimortalidade não é comum e isoladamente avaliado nos modelos de risco, mas é uma variável que reflete a severidade do trauma cirúrgico e a consequente resposta orgânica. Em alguns escores de risco, como o IRCR, considerou-se cirurgias de alto risco como uma das variáveis do modelo<sup>42</sup>. O modelo *Surgical Risk Scale* utilizou a classificação de porte cirúrgico inglesa *British United Provident Association* (BUPA) que divide os procedimentos em complexos maiores, maiores, intermediários e menores<sup>43</sup>. Já o *Surgical Mortality Probability Model* (SMP-M) classificou os procedimentos em maiores, intermediários e menores através de estimativas empíricas de mortalidade após ajustes para o ASA e a natureza emergencial ou eletiva<sup>32</sup>.

Uma das classificações mais lógicas foi utilizada por Donati, uma versão simplificada dos critérios cirúrgicos da *John Hopkins*, que leva em conta a potencial

invasão e o sangramento do procedimento, dividindo-os em três categorias: cirurgias de graus menor, moderado e maior<sup>35</sup>. No Brasil, a Associação Médica Brasileira (AMB) classifica os procedimentos como pequeno, médio, grande e especial. O HCPA não utiliza essa classificação, sendo permitidas diferentes nomenclaturas para procedimentos semelhantes, o que dificulta o agrupamento da severidade deles. Para fins de padronização, o grupo de pesquisa do Serviço de Anestesia e Medicina Perioperatória (SAMPE) do HCPA reuniu-se com especialistas da área cirúrgica a fim de classificar os procedimentos em três categorias de acordo com a severidade, o que é mostrado no Quadro 2.

**Quadro 2 - Classificação da Severidade Cirúrgica conforme revisão de literatura e consulta com especialistas**

Severidade	Definição	Procedimento-exemplos
Menor / Baixo Risco Cirúrgico	Mínimo risco, independente da anestesia e condição clínica do paciente; Procedimento minimamente ou moderadamente invasivo; Perda sanguínea estimada < 500 ml.	Cirurgia de Mama Apendicectomia Tireoidectomia Cirurgia Estética Laparoscopia Cistoscopia Tenorrafia
Intermediária / Intermediário Risco Cirúrgico	Risco Moderado independente da anestesia e condição clínica do paciente; Procedimento moderadamente invasivo; Perda sanguínea estimada entre 500 ml e 1500ml.	Colecistectomia Esofagomiotomia Histerectomia Colostomia Artrodese Cervical Simpatectomia Artrotomia de joelho Nefrectomia videolaparoscópica
Alta / Alto Risco Cirúrgico	Alto Risco, independente da anestesia e condição clínica do paciente; Procedimento altamente invasivo; Perda sanguínea estimada > 1500 ml.	Cirurgia Cardíaca Colectomia Esofagectomia Hepatectomia Lobectomia Pulmonar Microcirurgia para Tumor Intracraniano By-Pass Arterial Prostatectomia Radical

**Fonte:** Elaborado pela autora.

## 2.4 DEFINIÇÃO DE DESFECHOS

A cirurgia pode afetar diferentes setores da vida do paciente, muitas vezes interferindo além do curto espaço de tempo de recuperação pós-operatória. Incapacidades físicas transitórias ou permanentes, acometimento psicológico e psicosocial, prejuízos econômicos e à própria qualidade de vida são alguns exemplos. Assim, a mortalidade, embora seja um desfecho facilmente mensurável, pode não refletir integralmente o impacto e as consequências das estratégias adotadas no cuidado perioperatório. Nesse sentido, diferentes desfechos são mensurados por instrumentos de estratificação de risco disponíveis na literatura. A seguir, sumarizados no Quadro 3, apresentamos alguns desses principais desfechos comumente analisados no período pós-operatório.

**Quadro 3 - Desfechos avaliados no pós-operatório**

Tipo de desfecho	Mensuração	Observações
Mortalidade	<ul style="list-style-type: none"> <li>•Óbito transoperatório;</li> <li>•Óbito pós-operatório;</li> </ul>	Fácil mensuração, normalmente alvo de estudos observacionais
Morbidade	<ul style="list-style-type: none"> <li>•Incidência de complicações;</li> <li>•Escalas de complicações como escala POMS;</li> <li>•Internação em Unidade de Terapia Intensiva;</li> <li>•Reintervenção cirúrgica;</li> <li>•Taxa de <i>Failure to Rescue</i>;</li> <li>•Acionamento do TRR.</li> </ul>	Depende da definição de complicações e possibilidade de coleta dos dados
Desfechos centrados no paciente	<ul style="list-style-type: none"> <li>•Satisfação;</li> <li>•Tempo para reabilitação;</li> <li>•Independência;</li> <li>•Desfechos específicos para cada procedimento.</li> </ul>	Normalmente avaliado com questionários no pós-operatório; A maneira de coletar influencia a informação.
Desfechos econômicos	<ul style="list-style-type: none"> <li>•Tempo de internação hospitalar;</li> <li>•Reinternação hospitalar;</li> <li>•Custo associado a complicações e à permanência.</li> </ul>	O tempo de internação é uma medida indireta de custo.

**Fonte:** Elaborado pela autora.

## ♦ MORTALIDADE

A mortalidade relacionada à anestesia, assim como a pós-operatória em geral, teve expressiva redução nas últimas décadas. Melhorias nos campos da cirurgia, da anestesia, dos cuidados hospitalares, combinadas a um avanço na condição geral da saúde da população, fizeram com que a taxa global de mortalidade associada a uma variedade de tipos de procedimentos venha diminuindo com o tempo<sup>44</sup>.

Por ser de fácil mensuração e definição, a mortalidade é utilizada por muitas escalas tradicionais de risco como desfecho principal. No entanto, a variabilidade de aferição temporal desse indicador no pós-operatório pode dificultar a comparação entre diferentes instrumentos, visto que são encontrados estudos que avaliam mortalidade intra-hospitalar em 48 horas, 30 dias ou até um ano após a cirurgia. Complicações graves no período perioperatório, que levam à morte tardivamente, por exemplo, não entram nessa equação<sup>45</sup>.

## ♦ COMPLICAÇÕES PÓS-OPERATÓRIAS

A morbidade após a cirurgia tem sido tradicionalmente definida como a presença ou ausência de complicações pós-operatórias dadas por diagnósticos médicos específicos. A descrição e os métodos de mensuração de morbidade na literatura em geral são diversos. Sendo assim, tal diferença nos modos de aferição, baixa confiabilidade dos dados, ausência de definições claras sobre os desfechos, variabilidade na escolha dos instrumentos de avaliação são alguns fatores que dificultam a comparação entre os estudos e os sistemas de saúde. Afinal, a adequada definição e comunicação de eventos adversos é essencial para a interpretação dos resultados.

A estimativa precisa da ocorrência de complicações pós-operatórias pode ser difícil de ser realizada, com ocorrência estimada entre 3 e 17% dos casos. Um dos motivos para essa variabilidade é a ausência de um consenso sobre o que pode ser considerado uma complicação pós-operatória e sua severidade. Nesse sentido, algumas escalas e determinados levantamentos surgiram com o objetivo de padronizar e avaliar a ocorrência de morbidade pós-operatória<sup>46</sup>.

Em 1992, Clavien e colaboradores formularam uma escala, com quatro graus

de severidade das complicações pós-operatórias, baseada na terapêutica para seu tratamento e revalidada em uma coorte de 6.336 pacientes de cirurgia geral eletiva anos depois, em 2004. A graduação da severidade da complicação teve correlação com o tempo de internação hospitalar e a complexidade da cirurgia<sup>47</sup>.

Em 1999, Bennet-Guerreiro e colaboradores acompanharam prospectivamente 438 pacientes cirúrgicos em relação à ocorrência de complicações cirúrgicas pré-definidas no pós-operatório. O objetivo da *Postoperative Morbidity Survey* (POMS) era de identificar desde complicações potencialmente fatais até sinais sutis de morbidade pós-operatória. Logo, esse levantamento foi concebido para avaliar a ocorrência de indicadores de disfunção orgânica, de forma simples e sem necessidade de testes adicionais, em 9 domínios: pulmonar, renal, infeccioso, cardiovascular, neurológico, gastrointestinal, sítio cirúrgico, hematológico e dor/imobilidade. Portanto, a POMS é considerada um instrumento válido e confiável de descrição de morbidade pós-operatória em curto prazo<sup>48,49</sup>.

Aproximadamente 20% dos pacientes cirúrgicos irão desenvolver alguma complicação nos primeiros dias pós-operatórios, podendo essa ocorrer inclusive no pós-operatório imediato. No estudo REASON, quanto à análise de complicações pós-operatórias, Story e colaboradores observaram que na população cirúrgica acima de 70 anos a insuficiência renal aguda, a inflamação sistêmica e a internação não planejada em UTI estiveram associadas a maior mortalidade<sup>50</sup>. Tym e colaboradores analisaram eventos sugestivos de deterioração clínica ocorridos nos três primeiros dias pós-operatórios, encontrando 20% de ocorrências. A maioria dos eventos foi de natureza respiratória e circulatória, sendo comuns na SRPA e na enfermaria. Pacientes que apresentaram sedação excessiva, hipotensão e dessaturação nesse contexto tiveram uma maior probabilidade de atendimento pelo TRR, sugerindo a presença de sinais indicativos de disfunção orgânica<sup>51</sup>.

A identificação precoce dos sinais de disfunção orgânica pode impactar a ocorrência de desfechos potencialmente fatais no pós-operatório. Em um estudo que comparou taxas de complicações pós-operatórias e mortalidade, Ghaferi e colaboradores identificaram que hospitais com diferentes taxas de mortalidade apresentavam frequentemente complicações semelhantes, indicando que alguns possuem um melhor desempenho em reconhecer e tratar seus pacientes em risco<sup>52</sup>.

O fenômeno da morte decorrente de uma complicação no pós-operatório pode ser denominado com a expressão *failure to rescue*. Ela se refere a um

conceito, uma métrica e tem sido utilizada justamente para avaliar a capacidade de resposta dos hospitais frente a uma complicação, sendo um indicador de desempenho e qualidade na assistência ao paciente cirúrgico<sup>53</sup>.

#### ♦ INTERNAÇÃO EM TERAPIA INTENSIVA

A demanda por leitos de terapia intensiva frequentemente ultrapassa a capacidade de atendimento dos Serviços de Saúde. Aqueles pacientes a apresentar maior potencial relacionado à redução de morbimortalidade deveriam ser triados para as Unidades de Tratamento Intensivo. Se, por um lado, acredita-se que a internação nelas pode reduzir a mortalidade, por outro, exposição a patógenos nosocomiais, tratamentos agressivos, imobilidade, isolamento, alterações psíquicas, como *stress* e *delirium*, são fatores que podem aumentar esse risco<sup>54</sup>.

A identificação dos pacientes de alto risco com potencial benefício do tratamento em UTI é um desafio. Em estudo realizado no Reino Unido, Pearse e colaboradores identificaram que uma pequena parcela de pacientes de alto risco cirúrgico foi responsável por 80% dos casos de morte pós-operatória. Apenas uma minoria desses pacientes (menos de 15%) foi encaminhada diretamente à UTI após a cirurgia. As mais altas taxas de mortalidade foram observadas naqueles pacientes encaminhados primeiramente às enfermarias e transferidos tardivamente para UTI<sup>7</sup>. Em outro estudo do mesmo pesquisador, que acompanhou 46.539 pacientes cirúrgicos da Europa, foi constatada uma taxa de admissão planejada em UTI de apenas 5%. Admissões não planejadas estiveram associadas à alta taxa de mortalidade e 73% dos pacientes que morreram não foram admitidos na UTI em nenhum momento. Consequentemente, esses dados sugerem uma falha sistemática na alocação e no gerenciamento de recursos<sup>15</sup>.

Muitos fatores podem influenciar a transferência de um paciente para UTI, desde a disponibilidade de recursos técnicos e humanos até as diferenças socioeconômicas e culturais entre as regiões. Critérios objetivos, baseados em evidências, podem potencialmente auxiliar na identificação daqueles pacientes que terão o maior benefício com esse tipo de cuidado para redução de desfechos<sup>54,55</sup>.

Destacamos que ainda existe um debate em relação ao benefício na redução da mortalidade no paciente cirúrgico com a admissão em UTI. Enquanto alguns estudos exploram as altas taxas de mortalidade associadas a falhas de alocação

desse recurso para os pacientes de alto risco, outros não conseguem demonstrar benefícios na redução de desfechos. A grande variabilidade de fatores a interferir nas análises, como a estrutura dos serviços de saúde, as equipes de cuidados pós-cirúrgicos eficientes nas enfermarias, a presença de unidades semi-intensivas e as falhas na triagem dos pacientes, pode explicar, em parte, a falta de consenso relacionado ao assunto<sup>56</sup>.

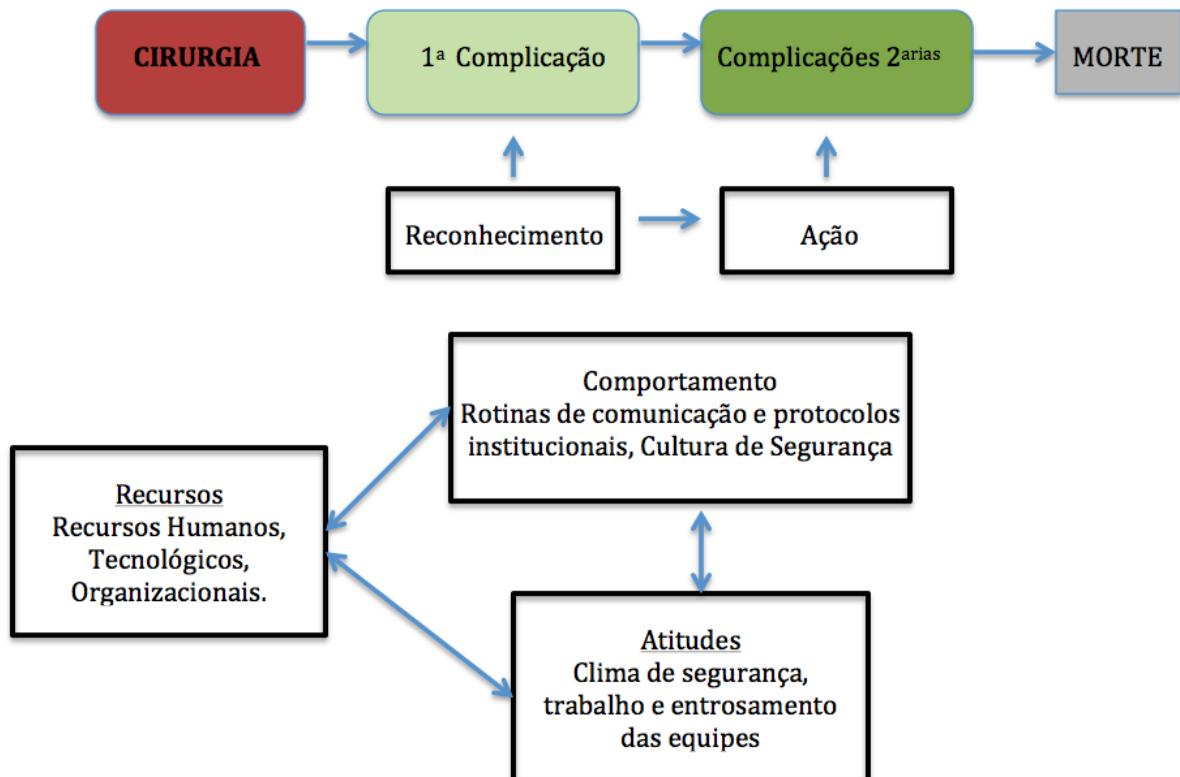
## 2.5 A INTEGRAÇÃO ENTRE ESTRUTURA, PROCESSO E DESFECHO NO PACIENTE CIRÚRGICO

A qualidade da assistência prestada ao paciente cirúrgico depende da integração entre a estrutura, isto é, como o cuidado é organizado, o processo, como esse cuidado é oferecido, e os resultados alcançados. A morbimortalidade cirúrgica pode variar conforme o fluxo assistencial em que o paciente está inserido, podendo ele sofrer as mais diferentes influências durante os estágios pré, trans e pós-operatório de acordo com o padrão hospitalar<sup>15,55</sup>. Estudos evidenciam que a experiência associada ao volume cirúrgico, a manutenção de uma linha de cuidado compatível com o risco do paciente, o reconhecimento precoce e a ativação do atendimento médico frente a uma complicação influenciam diretamente os desfechos no pós-operatório<sup>57</sup>. A mortalidade perioperatória muitas vezes é o resultado de uma cascata de eventos iniciada a partir de uma complicação, influenciada por fatores relacionados ao paciente, à cirurgia e efetividade do sistema em reconhecer e agir corretamente frente ao evento adverso<sup>25</sup>.

Apesar das evidências de que pacientes cirúrgicos admitidos tarde na UTI têm um pior prognóstico, apenas aproximadamente 1/3 daqueles considerados de alto risco recebem cuidados intensivos. Frequentemente, as Salas de Recuperação Pós-Anestésicas recebem esses pacientes, devendo fornecer o cuidado intensivo até que um leito esteja disponível<sup>55</sup>. Treinamento de equipe, adequação de processos e recursos devem garantir o melhor atendimento possível durante esse período.

A visão de que a atuação do anestesista restringe-se ao transoperatório remonta ao surgimento da especialidade e precisa ser revista. O conceito de medicina perioperatória engloba a implementação de linhas de cuidado e assistência multidisciplinar pré, trans e pós-operatória. A individualização de desfechos, o tempo

de reabilitação e retorno à funcionalidade, a redução de reinternação e satisfação do paciente são também exemplos de alvos assistenciais que devem ser priorizados nesse contexto.



**Figura 3** - Modelo Conceitual das dinâmicas organizacionais que podem afetar o resgate de complicações no período pós-operatório. **Fonte:** Adaptado de Ghaferi et al., 2017<sup>25</sup>.

## 2.6 INSTRUMENTOS PARA ESTRATIFICAÇÃO DE RISCO – A CONSTRUÇÃO DE UM MODELO PROGNÓSTICO

Deveríamos identificar o grupo de pacientes mais suscetível a complicações e à morte, a fim de nos auxiliar nas decisões referentes aos cuidados pré, trans e pós-operatórios, incluindo a necessidade ou não de recuperação em UTI. O escore de risco ideal deveria combinar simplicidade, acurácia, objetividade, além de ser aplicável a todos os pacientes, fornecendo uma informação individualizada<sup>9</sup>. No entanto, não existe um instrumento ideal que possa servir universalmente à predição de risco perioperatório, uma vez que os resultados dependem da combinação do risco intrínseco ao procedimento e das condições físicas do paciente<sup>58,57</sup>.

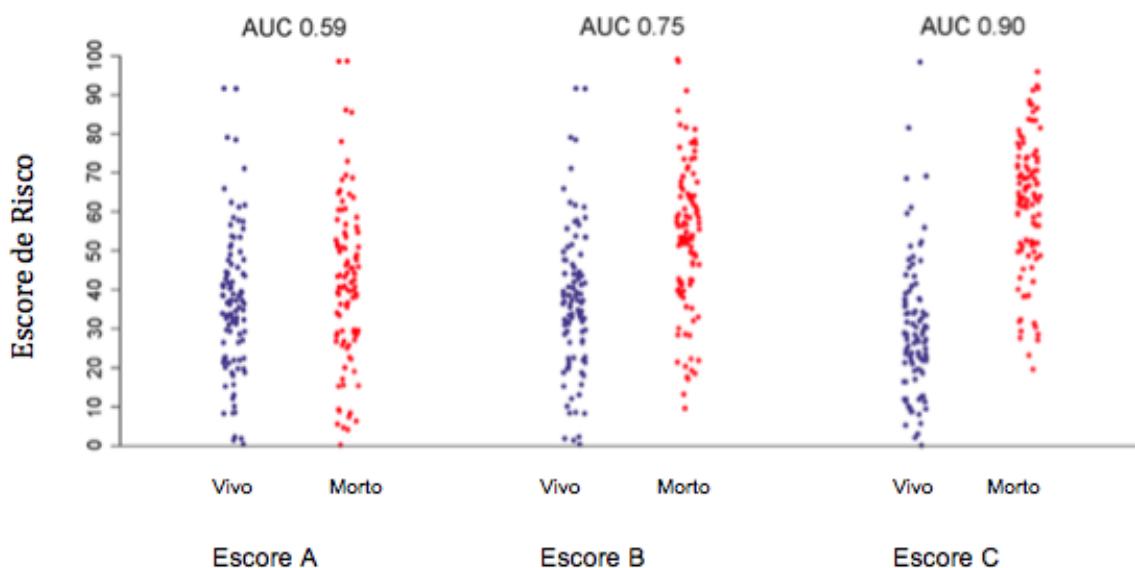
As ferramentas de estratificação de risco podem ser subdivididas em escores e modelos de risco. Um elemento comum entre essas ferramentas é o fato de, não raro, serem desenvolvidas a partir de análises multivariadas de fatores preditores para a ocorrência de determinado desfecho. Escores de risco geralmente atribuem diferentes pesos às variáveis preditoras do desfecho de interesse. Embora o paciente seja classificado em um estrato de risco, esses escores não fornecem uma probabilidade individualizada em relação à ocorrência do desfecho (exemplo – ICR).

Modelos de predição de risco fornecem uma probabilidade individualizada da ocorrência do desfecho através da análise dos dados do paciente em um modelo estatístico de predição de risco. Geralmente, esses modelos são desenvolvidos por meio da seleção de variáveis preditoras, incluídas em um modelo de regressão logística multivariada<sup>6,59</sup>. Embora eles forneçam uma informação teoricamente mais acurada em relação ao risco do paciente, tendem a uma maior complexidade para uso diário, muitas vezes necessitando de uma interface digital (exemplo – ACSNSQIP *Surgical Risk Calculator*).

Um modelo de estratificação de risco deve ser acurado, demonstrando uma boa capacidade discriminativa entre os indivíduos que apresentaram e os que não apresentaram o desfecho. Diferentes métodos podem ser utilizados para avaliar a *performance* geral, capacidade discriminativa, calibração e os índices de reclassificação clínica de um modelo prognóstico. O escore de *Brier*, por exemplo, informa a distância entre a probabilidade e a real ocorrência de um desfecho binário, sendo considerado uma medida geral de *performance*. Essa distância entre o predito e o observado está relacionada à qualidade de ajuste, sendo que valores menores indicam melhores modelos<sup>60</sup>. O melhor resultado do escore de *Brier* é zero (acurácia total) e o pior resultado possível é um.

Uma medida para avaliar a discriminação é a estatística C, área sob a curva (AUC) *Receiver Operating Characteristic* (ROC), que compara as probabilidades preditas entre indivíduos que apresentaram ou não o desfecho de interesse. Se as pontuações dos indivíduos com o desfecho forem todas mais altas, podemos dizer que o modelo discrimina perfeitamente, mesmo que as probabilidades preditas aferidas não concordem com as proporções reais de ocorrência<sup>61</sup>. Enquanto valores de AUROC de 0.5 indicam que a *performance* assemelha-se à obtida ao acaso, valores próximos a um indicam excelente capacidade discriminativa (figura 4)<sup>6,62</sup>.

Outra medida usualmente aferida é a calibração, que demonstra a concordância entre os eventos preditos e os observados, podendo ser acessada por diferentes testes estatísticos, como o Hosmer-Lemeshow. Esse teste compara em subgrupos as médias das probabilidades preditas esperadas com as proporções observadas entre indivíduos que desenvolveram ou não o desfecho<sup>63</sup>. A estatística desse teste tem uma distribuição qui-quadrado com  $g - 2$  graus de liberdade, em que  $g$  representa o número de subgrupos formado. Uma alternativa simples para demonstrar a calibração seria apresentar, em forma de tabela, a proporção de eventos observados e preditos nos diferentes estratos de risco<sup>6,64</sup>.



**Figura 4** - Demonstração da previsão de morte aferida por três escores hipotéticos em uma amostra de 200 pacientes. A probabilidade predita morte é medida em uma escala de 0 a 100. O escore A tem a maior concordância entre as probabilidades preditas dos indivíduos que morreram *versus* os que não morreram após a cirurgia. Logo, tem a menor capacidade discriminativa e menor AUROC. O escore C tem a menor concordância entre as probabilidades preditas entre vivos *versus* mortos, portanto uma maior capacidade discriminativa e maior AUROC. **Fonte:** Adaptado de Wijeyesundera, 2016<sup>6</sup>.

Ao adicionarmos ou modificarmos variáveis, podemos não observar alterações significativas na AUROC, principalmente se o modelo de risco for baseado em preditores fortes. Todavia, essas alterações podem resultar em mudanças na classificação de risco, que não necessariamente representam uma melhora da estratificação<sup>60</sup>. Uma forma de realizar essa avaliação é através da comparação da incidência observada de eventos nas células de uma tabela de reclassificação com a probabilidade predita do modelo original.

Pencina e colaboradores propuseram que indivíduos reclassificados, apresentando ou não o desfecho, deveriam ser considerados separadamente. Nos indivíduos com o desfecho, um aumento na classificação de risco significaria uma melhora, e uma diminuição nesse contexto implicaria uma piora da estratificação do modelo. Logo, naqueles pacientes sem o desfecho, temos o oposto<sup>60</sup>. O índice *Net Classification Improvement* (NRI) quantifica a melhora na reclassificação e é calculado pela soma das diferenças das proporções de indivíduos com e sem o desfecho, que se moveram para cima e para baixo na tabela de reclassificação<sup>63</sup>. A análise dessa reclassificação clínica pode informar o quanto a adição de um novo marcador pode melhorar um modelo prognóstico.

**Quadro 4 - Características das medidas de performance de escores e modelos de risco**

Aspecto	Medida	Características
Performance Geral	R <sup>2</sup> Brier	Melhor com pequenas distâncias entre Y e Ŷ Avalia calibração e discriminação.
Discriminação	Estatística C Curva ROC	Avalia a discriminação do modelo entre indivíduos com e sem desfecho, em ordem de classificação.
	Inclinação da Discriminação	Diferença na média das probabilidades entre os casos e controles. Fácil visualização (Box-Plot)
Calibração	Calibration-in-the-large	Compara médias de casos versus controles; aspecto essencial para validação externa.
	Hosmer-Lemeshow	Compara observados e preditos através de subgrupos (decimais) de probabilidade predita.
Reclassificação	Tabela de Reclassificação	Compara classificações de dois modelos (com e sem o desfecho).
	Net Reclassification Index (NRI)	Compara a classificação de dois modelos para mudança de desfecho, informando a reclassificação na direção correta.
Utilidade Clínica	Net Benefit (NB) Análise da Curva de Decisão (ACD)	Número de verdadeiros positivos identificados com versus sem o uso do modelo em um único limiar (NB) ou em faixa de valores (ACD)

**Fonte:** Adaptado de Steyerberg et al., 2013<sup>60</sup>

Em 2015, Collins e colaboradores publicaram um *check-list* de 22 itens com o objetivo de melhorar a descrição e transparência dos dados e das metodologias utilizadas em publicações de modelos multivariados de prognóstico e diagnóstico. Além de medidas de acurácia e calibração, o *Transparent Reporting of Multivariable*

*Prediction Model for Individual Prognosis or Diagnosis* (TRIPOD Statement) recomenda, além da validação interna, a externa do modelo em uma amostra diferente do desenvolvimento. Essa validação externa pode ser realizada pelos mesmos investigadores, ou não, utilizando uma amostra diferente de indivíduos, coletada em tempo (validação temporal) e/ou local distintos, podendo utilizar o mesmo modelo com diferentes desfechos, contextos e participantes (por exemplo, modelo desenvolvido na população adulta e adaptado para uso em crianças)<sup>62</sup>.

Além da acurácia prognóstica, esperamos que um instrumento de estratificação de risco seja simples e acessível, possibilitando sua incorporação na prática clínica diária. Modelos altamente acurados, porém extremamente complexos, correm o risco de ser subutilizados, servindo apenas como exercício acadêmico.

## 2.7 COMPARAÇÃO ENTRE DIFERENTES MODELOS E ESCORES DE RISCO

Talvez um dos escores de risco mais conhecidos e populares no meio anestésico-cirúrgico seja a classificação da *American Society of Anesthesiologists*, ASA-PS. A simplicidade do seu uso e a correlação com desfechos adversos em inúmeros estudos fizeram com que fosse amplamente aceita na prática clínica. Como limitações, essa escala não fornece probabilidade de risco individual, não inclui variáveis relacionadas ao procedimento cirúrgico, é subjetiva e apresenta, no mínimo, uma moderada variabilidade entre avaliadores<sup>9,31,6</sup>. Moreno e colaboradores analisaram uma coorte de 45.666 pacientes submetidos à cirurgia não cardíaca na Europa (dados do estudo *European Outcome Study* (EUSOS)) com o objetivo de analisar a relação entre classificação ASA-PS e a mortalidade pós-operatória. Os autores evidenciaram que, apesar de haver uma relação crescente com a mortalidade, a capacidade discriminativa na amostra foi modesta (AUROC 0.658, IC 95% 0.642-0.677). A escala ASA-PS conseguiu discriminar o grupo de alto risco na amostra, entretanto a pior *performance* discriminativa ocorreu no grupo considerado de baixo risco (ASA I e ASA II)<sup>33</sup>.

Determinados escores levam em conta tanto dados do pré-operatório quanto do intra-operatório, o que dificulta a construção do risco prévio ao procedimento, como o escore *Physiological and Operative Severity Score for the Enumeration of Mortality and Morbidity* (POSSUM). Desenvolvido por Copeland e colaboradores em 1991, esse escore é constituído por 18 variáveis (12 relacionadas ao *status*

fisiológico e seis à cirurgia) e avalia os desfechos morbidade e mortalidade pós-operatória. O escore superestima a ocorrência do desfecho mortalidade em pacientes considerados de baixo risco, o que gerou o desenvolvimento do Portsmouth-POSSUM (P-POSSUM). Diversas versões do escore foram analisadas na tentativa de individualizar e aumentar a precisão dele, como na cirurgia colo-retal (Cr-POSSUM), vascular (V-POSSUM) e na de esôfago (O-POSSUM). Apesar da variabilidade de precisão do escore nas diferentes populações cirúrgicas, o POSSUM é internacionalmente validado para predição de risco individual<sup>59,9,65,66</sup>.

Alguns modelos de risco, como o criado pelo *American College of Surgeons National Surgical Quality Improvement Program* (ACSNSQIP), apresentam o resultado de probabilidades de morte e complicações específicas com alta acurácia. O ACSNSQIP *Surgical Risk Calculator* foi desenvolvido através da análise dos dados de 393 hospitais americanos, inclui 21 variáveis preditoras para oito desfechos. A calculadora de risco cirúrgico pode ser acessada através de uma página da web. Entretanto, essa ferramenta incorporou um grande número de variáveis clínicas e cirúrgicas, necessitou de acesso a um software para o cálculo e foi formulada com uma base de dados do sistema de saúde americano, o que dificulta sua aplicabilidade externa<sup>67,59,9</sup>.

O escore *Surgical Mortality Probability Model* (S-MPM) foi desenvolvido com o intuito de ser simples e aplicável à beira do leito, utilizando informações facilmente coletadas. Glance e colaboradores utilizaram o banco de dados do ACSNSQIP em uma coorte de 298.772 pacientes. O escore incorpora três variáveis preditoras: classificação ASA-PS, severidade da cirurgia e caráter emergencial ou eletivo. Cada variável tem um peso atribuído e o valor final do escore é dado pela soma dos pesos. O S-MPM apresentou boa performance estatística, mas foi elaborado a partir da análise retrospectiva dos dados sem validação para outras populações<sup>32</sup>.

O modelo de estratificação de risco *Surgical Outcome Risk Tool* (SORT) foi desenvolvido através da análise de dados de uma coorte de 16.788 pacientes de 326 hospitais do *National Health Service* (NHS) do Reino Unido. Esse modelo utilizou seis variáveis coletadas no pré-operatório, fornecendo a probabilidade de morte em até 30 dias<sup>34</sup>. Recentemente, o modelo foi revalidado externamente em uma coorte de pacientes submetidos à cirurgia de quadril, apresentando apenas uma moderada acurácia na predição de morte em 30 dias (AUROC 0.70)<sup>68</sup>.

**Quadro 5 - Modelos e Escores de Risco**

(continua)

Modelo	Variáveis incluídas no modelo	Desfecho	População	AUROC (IC)	Comentários
SORT model <sup>34</sup>	<ul style="list-style-type: none"> <li>•ASA</li> <li>•Natureza da cirurgia</li> <li>•Especialidade de alto risco</li> <li>•Severidade Cirúrgica</li> <li>•Câncer</li> <li>•Idade</li> </ul>	Risco predito de morte em 30 dias	Cirurgia não-cardíaca (n=16.788)	0,91 (0,88-0,94)	Estudo multicêntrico do Reino Unido que usou uma classificação específica de severidade cirúrgica. A AUROC deste modelo comparado à <i>Surgical Risk Scale</i> e ASA-PS foi superior. Necessita para cálculo um app web-based
Surgical Mortality Probability Model, (SMP-M) <sup>32</sup>	<ul style="list-style-type: none"> <li>•Severidade cirúrgica</li> <li>•ASA</li> <li>•Natureza da cirurgia</li> </ul>	Mortalidade em 30 dias	Pacientes de cirurgias em geral, (n=298.772)	0.897 na coorte de validação	Baseado no <i>American College of Surgeons Program (ACS NSQIP)</i> . Apresenta boa discriminação comparado ao ACS NSQIP <i>Surgical Risk Calculator</i> .
mE-PASS <sup>69</sup>	<ul style="list-style-type: none"> <li>•Idade</li> <li>•Doença pulmonar severa</li> <li>•Doença cardíaca severa</li> <li>•Diabetes mellitus</li> <li>•ASA-PS</li> <li>•Status funcional</li> <li>•Procedimento cirúrgico</li> </ul>	Mortalidade intra-hospitalar e mortalidade em 30 dias	Pacientes de cirurgias em geral, (n=5.272)	Mortalidade intra-hospitalar: 0.86 (0.79-0.92) Mortalidade em 30 dias: 0.81 (0.66-0.96)	Modelo derivado do <i>Japanese National Health Care Reimbursement System</i> . Boa acurácia em relação a modelos que incluíam variáveis intra-operatórias (E-PASS and POSSUM).
IRCR (Lee Cardiac Index) <sup>70</sup>	<ul style="list-style-type: none"> <li>•Cirurgia de Alto Risco</li> <li>•Cardiopatia isquêmica</li> <li>•Insuficiência cardíaca</li> <li>•Doença cerebrovascular</li> <li>•Creatinina &gt; 2 mg/dL</li> <li>•Diabetes mellitus insulino-dependente</li> </ul>	Mortalidade de causas cardíacas em até 30 dias.	Cirurgia não-cardíaca (n=108.593)	Mortalidade de causa cardíaca: 0.63	Desfecho avaliado foi morte de causas cardíacas. A classificação severidade da cirurgia em apenas duas classes de risco parece sub-ótima. Com o remodelamento incluindo a variável idade e variáveis relacionadas a cirurgia a AUROC= 0.85.
Surgical Risk Score <sup>35</sup>	<ul style="list-style-type: none"> <li>•ASA</li> <li>•Severidade da cirurgia</li> <li>•Natureza da cirurgia</li> <li>•Idade</li> </ul>	Mortalidade intra-hospitalar	Cirurgias em geral, (n=1.849)	0.88 (0.83-0.93)	Desenvolvido e validado na Itália. Subsequente estudo encontrou moderada capacidade preditiva de morte intra-hospitalar. <sup>70</sup>

**Quadro 5 - Modelos e Escores de Risco**

(conclusão)

ASA PS <sup>35</sup>	•ASA	Mortalidade Intra-hospitalar	Pacientes de cirurgia em geral (n=1.849)	0.81 (0.79-0.82)	A classificação ASA-PS é utilizada desde 1941. Nesta coorte, teve boa acurácia mesmo sendo o único preditor.
Charlson <sup>71</sup> (ICC)	•Original: 19 comorbidades clínicas. •Update: 12 comorbidades clínicas	Mortalidade em 30 dias; Mortalidade em 1 ano	Pacientes Hospitalares	Original: 0.881 Update: 0.884	Desenvolvido para prever morte em 1 ano. Não considera a cirurgia. Nesta coorte, o escore original e o atualizado mostraram performance semelhante
Surgical Risk Scale <sup>43</sup>	•ASA •Cirurgia – (menor, intermediária, maior, maior plus, maior complexa) •Natureza da cirurgia (eletiva, agendada, urgente, emergência)	Mortalidade Intra-hospitalar	Cirurgia Gastrointestinal, Vascular, Trauma (n=3.144)	0.95 (0.93-0.97)	Incorpora subclassificações específicas: <i>Confidential Enquiry into Perioperative Deaths (CEDOP)</i> e <i>British United Provident Association classification (BUPA)</i> . Cirurgias realizadas por apenas 3 cirurgiões nesta coorte e validado em apenas um centro.

**Fonte:** Elaborado pela autora.

## 2.8 ÍNDICE DE RISCO CARDÍACO REVISADO

O IRCR é um sistema de pontuação utilizado para prever o risco de eventos cardíacos maiores após cirurgia não cardíaca. Constitui-se ferramenta simples, validada e que considera o porte cirúrgico, porém avalia apenas um órgão específico e não o risco global de complicações<sup>9,57</sup>.

Lee e colaboradores identificaram, através de um estudo de coorte prospectivo, seis fatores de risco relacionados à ocorrência de complicações cardíacas no pós-operatório de cirurgia não cardíaca. Os fatores de risco identificados por meio de uma análise de regressão logística na coorte estudada foram: cirurgia de alto risco (intraperitoneal, intratorácica e vascular supra-inguinal), histórias de doença cardíaca isquêmica, insuficiência cardíaca, e cerebrovascular; diabetes insulino-dependente e creatinina sérica acima de 2 mg/dL. Os desfechos

analisados foram a ocorrência de infarto do miocárdio, edema pulmonar, fibrilação ventricular ou parada cardíaca e bloqueio cardíaco completo. Os autores encontraram taxas de ocorrência dos desfechos de 0.4%, 0.9%, 7% e 11% de acordo com a presença de 0, 1, 2, 3 ou mais fatores de risco respectivamente (tabela 3)<sup>42</sup>. O escore de risco apresentou uma boa capacidade discriminativa para eventos cardíacos entre pacientes de alto e baixo risco em cirurgia não cardíaca.

Em 2005, Boersma e colaboradores analisaram uma coorte de 108.593 pacientes submetidos à cirurgia não cardíaca. O desfecho analisado foi morte de causas cardíacas. O ICR apontou uma baixa capacidade discriminativa na amostra (AUROC 0.63). Adicionando a idade e estratificação da severidade da cirurgia como variáveis preditoras no modelo, houve uma melhora da performance estatística (AUROC 0.85)<sup>70</sup>.

**Tabela 2 - Índice de Risco Cardíaco Revisado**

Classes de Risco*	Lee et al. (AUROC 0.806)	Boersma et al. (AUROC 0.63)
I	0,4% (0.05-1.5)	1% (1.7-2.4)
II	0,9% (0.3-2.1)	2% (1.7-2.4)
III	7% (3.9-10.3)	5.1% (3.8-6.7)
IV	11% (5.8-18.4)	11% (7.7-15.8)

Fatores de Risco: Cirurgia de Alto Risco, Doença Cardíaca Isquêmica, História de Insuficiência Cardíaca Congestiva, História de Doença Cerebrovascular, Diabetes Insulino-dependente, Creatinina Sérica Pré-operatória > 2.0mg/dL

\* Classe I= 0 Fatores de Risco; Classe II= 1 Fator de Risco; Classe III= 2 Fatores de Risco, Classe IV ≥ 3 Fatores de Risco

**Fonte:** Elaborado pela autora com informações de Boersma et al., 2005<sup>70</sup> e Lee et al., 1999<sup>42</sup>.

Em 2010, Ford e colaboradores realizaram uma revisão sistemática a fim de avaliar a capacidade preditiva do ICR em diferentes estudos, para os desfechos complicações cardíacas maiores e morte hospitalar em até 30 dias pós-operatórios. Os autores confirmaram a capacidade moderada de discriminar pacientes de baixo *versus* alto risco para complicações cardíacas em um grupo heterogêneo de cirurgias. No entanto, quando analisada a mortalidade geral em cirurgias não cardíacas de alto risco, o índice apresentou baixa capacidade discriminativa. Analisando os pacientes submetidos à cirurgia vascular, o índice também não apresentou a mesma *performance*, provavelmente porque a cirurgia em si e a doença aterosclerótica avançada em um grupo homogêneo já representavam fatores de risco comum aos indivíduos<sup>72</sup>.

Atualizações e adaptações buscando uma melhor *performance* do IRCR foram feitas nos últimos anos. Utilizando um grande banco de dados do NSQIP, foi desenvolvido um modelo de predição de risco para Infarto do Miocárdio e Parada Cardíaca (MICA) em até 30 dias pós-operatórios de cirurgia não cardíaca. O modelo final foi composto pelas seguintes variáveis: ASA-PS, dependência funcional, idade avançada, creatinina >1,5 mg/dL e tipo de cirurgia. O escore NSQIP-MICA apresentou estatística C superior ao IRCR na amostra de validação, 0,874 e 0,747 respectivamente. Quando analisada a estatística C em amostra de pacientes submetidos à cirurgia vascular e aórtica não cardíaca, o escore também foi superior ao IRCR ( 0,75 versus 0,591)<sup>73</sup>.

Em uma nova análise realizada em uma coorte de 9519 pacientes submetidos à cirurgia não cardíaca, o IRCR apresentou *performance* similar ao estudo original, com taxas de ocorrência dos desfechos (complicações cardíacas maiores) de 0,5%, 2,6%, 7,2% e 14,4% para 0,1, 2 e 3 ou mais fatores de risco<sup>74</sup>. Os autores encontraram uma incidência maior de infarto do miocárdio na coorte estudada, o que pode refletir o avanço no uso de biomarcadores (troponina) no diagnóstico da isquemia miocárdica perioperatória<sup>74,75,76</sup>.

Apesar de suas limitações, como não incluir a idade, cirurgia de urgência e possuir uma heterogeneidade na categorização da cirurgia de alto risco, o IRCR ainda é a ferramenta de avaliação de risco de complicações cardiovasculares após cirurgia não cardíaca recomendada<sup>77</sup>. Embora as complicações cardíacas não sejam as mais frequentes no período pós-operatório, são elas as associadas às maiores taxas de mortalidade e ao impacto a longo prazo.

## 2.9 ÍNDICE DE COMORBIDADES DE CHARLSON

O ICC foi publicado em 1987 e desde então tem sido utilizado em diferentes estudos, populações cirúrgicas e clínicas como ferramenta validada para predição de mortalidade<sup>9,71</sup>. Esse índice foi desenvolvido através da análise das comorbidades e da mortalidade de uma coorte de pacientes que completaram um ano de *follow-up*. Charlson e colaboradores desenvolveram o ICC com diferentes pesos atribuídos às comorbidades conforme os riscos relativos de morte nesse período. As doenças que apresentaram risco relativo de morte inferior a 1,2 foram excluídas da composição, o que resultou em uma lista de 17 comorbidades (Tabela

4)<sup>78</sup>.

O índice foi testado em uma nova coorte de 685 pacientes com câncer de mama na predição de morte devido às comorbidades. A idade mostrou-se uma variável de impacto na mortalidade, o que levou a uma validação de um índice combinado de comorbidade e idade<sup>79</sup>. O Índice de Comorbidades de Charlson foi revisado por Quan e colaboradores, com a análise de dados de hospitais de seis países, encontrando-se *performance* similar ao índice original por prever morte intra-hospitalar em 30 dias e 1 ano<sup>71</sup>.

No estudo de coorte retrospectivo, em um hospital de nível terciário, o ICC apresentou melhor capacidade discriminativa que a classificação ASA-PS em prever morte intra-hospitalar pós-operatória em uma amostra de 182,886 pacientes ( $AUROC_{ICC}$  0,865 e  $AUROC_{ASA-PS}$  0,833). Associando o ICC aos fatores de risco, como idade, sexo, cirurgia eletiva *versus* urgência, tipo de cirurgia (intra-abdominal, intratorácica, intracraniana) e transfusão intra-operatória, o escore resultante – *Surgical Mortality Score* – apresentou melhor performance que o ICC e ASA-PS na predição de morte pós-operatória<sup>80</sup>. Apesar de ser relativamente simples de aplicar, o ICC tem a desvantagem de não levar em conta dados da cirurgia nem possuir um potencial viés na aferição das comorbidades (subjetividade e fonte de coleta da informação)<sup>59,6</sup>.

**Tabela 3 - Pesos e Comorbidades do Índice de Comorbidades de Charlson****Índice de Comorbidades de Charlson – Pesos e Comorbidades**

<b>1</b>	<b>2</b>	<b>3</b>	<b>6</b>
Infarto do Miocárdio	Hemiplegia	Doença hepática moderada a severa	Tumor sólido metastático
Insuficiência Cardíaca Congestiva	Diabetes com lesão em órgão alvo		SIDA
Doença Vascular Periférica	Neoplasia		
Doença Cerebrovascular	Doença Renal moderada a severa		
DPOC			
Doença do tecido conectivo			
Doença ulcerosa péptica			
Diabetes sem lesão em órgão alvo			
Doença hepática leve			
Demência			

DPOC: doença pulmonar obstrutiva crônica; SIDA: síndrome da imunodeficiência humana adquirida.

**Fonte:** Adaptado de Barnett et al., 2011<sup>9</sup>.

### 3 JUSTIFICATIVA

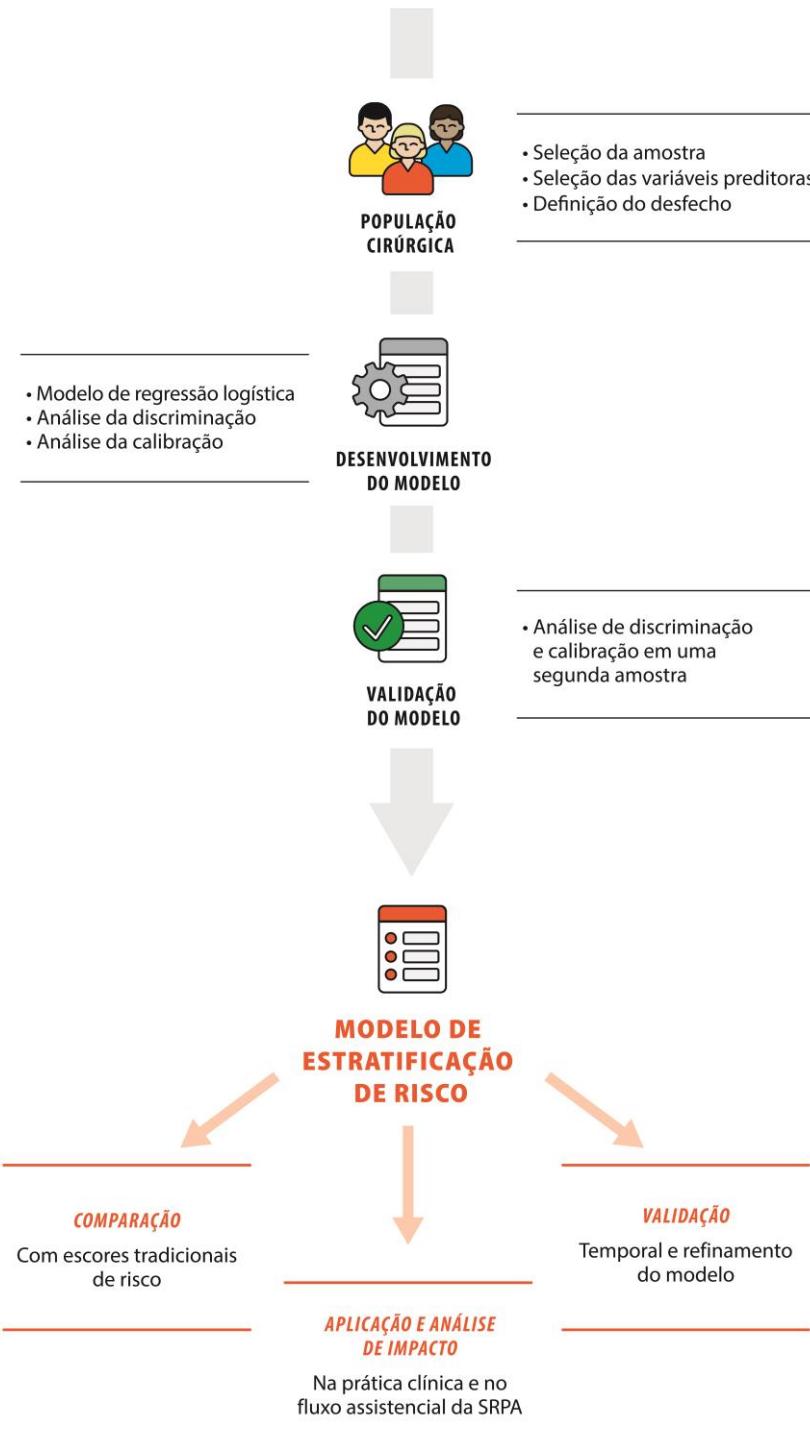
A medicina perioperatória visa ao cuidado integral do paciente candidato à cirurgia, desde a decisão de operar até sua reabilitação a longo prazo. Conhecer os indicadores nacionais de complicações e mortes no perioperatório e usar instrumentos apropriados para mensurá-los é o passo fundamental para o desenvolvimento de posteriores ações e programas voltados à melhoria dos desfechos nessa população. Sabemos que uma minoria de pacientes considerados de alto risco é responsável pela maioria das complicações e mortes no pós-operatório, portanto identificar esse grupo é essencial.

A estratificação de risco permite aos profissionais envolvidos no cuidado do paciente cirúrgico (cirurgiões, anestesistas, clínicos e equipe de enfermagem) considerarem o risco predito de complicações e morte de forma objetiva nas tomadas de decisões. A inclusão dos pacientes de maior risco em linhas assistenciais específicas de cuidado multiprofissional pode trazer alguns benefícios potenciais na redução de desfechos. Além disso, possibilita a instrumentalização para decisões sobre o uso racional de monitorização invasiva, comanejo clínico e alocação pós-operatória em terapia intensiva. Desse modo, esperamos que a estratificação otimize a comunicação do risco aos pacientes e seus familiares e entre os profissionais responsáveis pelas transferências de cuidado desses pacientes cirúrgicos.

Embora existam diversas ferramentas para estratificação de risco, ainda não dispomos de um modelo simples, acessível, abrangente, com variáveis pré-operatórias de coleta factível, o qual seja validado e acurado para prever os desfechos na população brasileira. Nossa proposta visa, pois, preencher essa lacuna, consolidando um modelo de probabilidade de morte no pós-operatório que possa estratificar os pacientes cirúrgicos e alicerçar condutas para melhorar os processos assistenciais. Em outras palavras, almejamos que seja consolidada uma linha de pesquisa a partir desta tese, focada em ampliar a visibilidade do paciente cirúrgico, assim como sinalizar a urgente necessidade de programas nacionais em busca da qualidade assistencial perioperatória em diferentes instâncias. Afirmamos isso justamente por considerar a magnitude das consequentes complicações nos pacientes de alto risco.

## 4 MARCO TEÓRICO

Figura esquemática dos marcos conceituais e processos do estudo.



**Figura 5 - Marco Teórico.** **Fonte:** Elaborado pela autora.

## 5 OBJETIVOS

### 5.1 OBJETIVO PRINCIPAL

Desenvolver uma ferramenta de estratificação de risco pré-operatório simples, objetiva, abrangente, validada e acurada, que avalie aspectos relacionados ao paciente e à cirurgia, sendo incorporada na prática clínica diária.

### 5.2 OBJETIVOS SECUNDÁRIOS

#### **5.2.1 ESTUDO 1 - Desenvolvimento e validação de um modelo de risco pré-operatório para morte pós-operatória: Modelo SAMPE**

- ◆ Com dados do HCPA, desenvolver um modelo pré-operatório de probabilidade de óbito intra-hospitalar em até 30 dias, utilizando quatro variáveis preditoras: idade, classificação ASA-PS, severidade da cirurgia e caráter da cirurgia (eletiva *versus* urgente/emergencial). Além disso, avaliar o impacto das variáveis preditoras na ocorrência do desfecho e analisar a acurácia e calibração do modelo resultante;
- ◆ Validar o modelo desenvolvido em uma outra coorte de pacientes cirúrgicos do HCPA;
- ◆ Avaliar a alocação pós-operatória em leito de Terapia Intensiva no grupo de pacientes considerados de alto risco pelo Modelo SAMPE e o impacto desse modelo na mortalidade.

#### **5.2.2 ESTUDO 2 - Comparação entre o modelo de Estratificação de risco cirúrgico – Modelo SAMPE –, o ICR e o ICC como preditores de mortalidade durante a internação hospitalar até 30 dias**

- ◆ Comparar a acurácia do modelo com o ICR e o ICC na predição de morte intra-hospitalar em até 30 dias após a cirurgia;
- ◆ Avaliar a associação entre o modelo de risco SAMPE e a presença de morbidade no pós-operatório identificada pela escala POMS.

### **5.2.3 ESTUDO 3 - Avaliação prospectiva do impacto da incorporação do modelo de estratificação de risco pré-operatório (Modelo SAMPE) no fluxo pós-operatório e na incidência de chamadas do TRR**

- ♦ Incorporar o Modelo SAMPE na rotina de avaliação pré-operatória dos pacientes cirúrgicos acima de 16 anos do HCPA;
- ♦ Identificar os pacientes admitidos na SRPA conforme a classe de risco e implementar um *check-list* diferenciado de alta para os considerados de alto risco pelo Modelo SAMPE;
- ♦ Comparar a proporção de chamadas do TRR em 48 horas e 30 dias pós-operatórios, antes e depois da incorporação do SAMPE, nos diferentes estratos de risco desse Modelo;
- ♦ Comparar a taxa de mortalidade pós-operatória intra-hospitalar antes e depois da incorporação do Modelo SAMPE;

### **5.2.4 ESTUDO 4 - Validação e refinamento do Modelo SAMPE: desenvolvimento do Modelo SAMPE 2**

- ♦ Validar e refinar o Modelo SAMPE em uma nova coorte recente de pacientes cirúrgicos acima de 16 anos;
- ♦ Avaliar a capacidade discriminativa e a calibração do novo modelo desenvolvido, comparando-o ao original em relação ao desfecho morte intra-hospitalar em até 30 dias pós-operatórios.

## 6 REFERÊNCIAS BIBLIOGRÁFICAS

1. Bartels K, Karhausen J, Clambey E, Grenz A, Eltzschig H. Perioperative Organ Injury. *Anesthesiology*. 2014;119(6):1474-1489. doi:10.1097/ALN.000000000000022.
2. Pearse RM, Holt PJE, Grocott MPW. Managing perioperative risk in patients undergoing elective non-cardiac surgery. *BMJ*. 2011;343(d5759):734-740. doi:10.1136/bmj.d5759
3. Grocott MPW, Pearse RM. Perioperative medicine: The future of anaesthesia? *Br J Anaesth*. 2012;108(5):723-726. doi:10.1093/bja/aes124
4. Vetter TR, Boudreaux AM, Jones KA, Hunter JM, Pittet JF. The perioperative surgical home: How anesthesiology can collaboratively achieve and leverage the triple aim in health care. *Anesth Analg*. 2014;118(5):1131-1136. doi:10.1213/ANE.0000000000000228
5. Grocott MPW, Plumb JOM, Edwards M, Fecher-Jones I, Levett DZH. Re-designing the pathway to surgery: better care and added value. *Perioper Med*. 2017;6(9):1-7. doi:10.1186/s13741-017-0065-4
6. Wijeysundera DN. Predicting outcomes: Is there utility in risk scores? *Can J Anaesth*. 2016;63(2):148-158. doi:10.1007/s12630-015-0537-2
7. Pearse RM, Harrison DA, James P, et al. Identification and characterisation of the high-risk surgical population in the United Kingdom. *Crit Care*. 2006;10(3):1-6. doi:10.1186/cc4928
8. Stiegler MP, Tung A. Cognitive Processes in Anesthesiology Decision Making. *Anesthesiology*. 2014;120(1):204-217.
9. Barnett S, Moonesinghe SR. Clinical risk scores to guide perioperative management. *Postgr Med J*. 2011;87:535-542. doi:10.1136/pgmj.2010.107169
10. Royston P, Moons KGM, Altman DG, Vergouwe Y. Prognosis and prognostic research: Developing a prognostic model. *BMJ*. 2009;338:1373-1377. doi:10.1136/bmj.b604
11. Altman DG, Vergouwe Y, Royston P, Moons KGM. Prognosis and prognostic research: Validating a prognostic model. *BMJ*. 2009;338:1432-1435. doi:10.1136/bmj.b605
12. Moons KGM, Altman DG, Vergouwe Y, Royston P. Prognosis and prognostic research: Application and impact of prognostic models in clinical practice. *BMJ*. 2009;338:1487-1490. doi:10.1136/bmj.b606
13. Weiser TG, Regenbogen SE, Thompson KD, et al. An estimation of the global volume of surgery: a modelling strategy based on available data. *Lancet*. 2008;372:139-144. doi:10.1016/S0140-6736(08)60878-8
14. The International Surgical Outcomes Study group. Global patient outcomes after elective surgery: Prospective cohort study in 27 low-, middle- and high-income countries. *Br J Anaesth*. 2016;117(5):601-609. doi:10.1093/bja/aew316
15. Pearse RM, Moreno RP, Bauer P, et al. Mortality after surgery in Europe: a 7 day cohort study. *Lancet*. 2011;380:1059-1065. doi:10.1016/S0140-6736(12)61148-9

16. Sankar A, Scott Beattie W, Wijeysundera DN. How can we identify the high-risk patient? *Curr Opin Crit Care.* 2015;21(4):328-335.  
doi:10.1097/MCC.0000000000000216
17. Shah N, Hamilton M. Clinical review: Can we predict which patients are at risk of complications following surgery? *Crit Care.* 2013;17(3):1-8.  
doi:10.1186/cc11904
18. Priebe H-J. The aged cardiovascular risk patient. *Br J Anaesth.* 2000;85(5):763-778. doi:10.1093/bja/85.5.763
19. Merani S, Payne J, Padwal RS, Hudson D, Widder SL, Khadaroo RG. Predictors of in-hospital mortality and complications in very elderly patients undergoing emergency surgery. *World J Emerg Surg.* 2014;9(1):43.  
doi:10.1186/1749-7922-9-43
20. Makary MA, Segev DL, Pronovost PJ, et al. Frailty as a Predictor of Surgical Outcomes in Older Patients. *ACS.* 2010;210(6):901-908.  
doi:10.1016/j.jamcollsurg.2010.01.028
21. Jin F, Chung F. Minimizing perioperative adverse events in the elderly. *Br J Anaesth.* 2001;87(4):608-624. doi:10.1186/cc11904
22. Gajdos C, Kile D, Hawn MT, Finlayson E, Henderson WG, Robinson TN. Advancing Age and 30-Day Adverse Outcomes After Nonemergent General Surgeries. *JAGS.* 2013;61:1608-1614. doi:10.1111/jgs.12401
23. Jonathan A, Ms C, Alexander KP, et al. Frailty Assessment in the Cardiovascular Care of Older Adults. *JACC.* 2014;63(8):747-762.  
doi:10.1016/j.jacc.2013.09.070
24. Boddaert J, Raux M. et al. Perioperative management of elderly patients with hip fracture. *Anesthesiology.* 2014;121(6):1336-1341.  
doi:10.1136/bmj.333.7557.27
25. Ghaferi AA, Dimick JB, Arbor A, Arbor A, Arbor A. The importance of teamwork, communication, and culture in failure to rescue in the elderly Amir. *Br J Surg.* 2017;103(2):1-10. doi:10.1002/bjs.10031.
26. Stefani LP, Gamermann P, Backof A, et al. Perioperative anesthesia related mortality: a retrospective cohort study with 11,562 anesthetic procedures. *J Clin Anesth.* 2018;49:79-86.doi: 10.1186/cc11904
27. Saklad M. Grading of Patients for Surgical Procedures. *Anesthesiology.* 1941;2:281-284.doi: 10.1186/cc11904
28. Sankar A, Johnson SR, Beattie WS, Tait G, Wijeysundera DN. Reliability of the American Society of Anesthesiologists physical status scale in clinical practice. *Br J Anaesth.* 2014;113(April):424-432. doi:10.1093/bja/aeu100
29. Park J, Kim D, Kim B, Kim Y. The American Society of Anesthesiologists score influences on postoperative complications and total hospital charges after laparoscopic colorectal cancer surgery. *Medicine (Baltimore).* 2018;97(18):1-6.  
doi:10.1097/MD.00000000000010653
30. Wolters U, Wolf T, Stützer H, Schröder T. ASA classification and perioperative variables as predictors of postoperative outcome. *Br J Anaesth.* 1996;77:217-222.doi: 10.1186/cc11904

31. Hopkins TJ, Raghunathan K, Barbeito A, et al. Associations between ASA Physical Status and postoperative mortality at 48 h: a contemporary dataset analysis compared to a historical cohort. *Perioper Med.* 2016;5(29):1-6. doi:10.1186/s13741-016-0054-z
32. Glance LG, Lustik SJ, Hannan EL, et al. The Surgical Mortality Probability Model. *Ann Surg.* 2012;255(4):696-702. doi:10.1097/SLA.0b013e31824b45af
33. Moreno, Rui P; Pearse,R; Rhodes A. American Society of Anesthesiologists Score: still useful after 60 years? Results of the EuSOS Study. *Rev Bras Ter Intensiva.* 2015;27(1):105-112. doi:10.5935/0103-507X.20150020
34. Protopapa KL, Simpson JC, Smith NCE, Moonesinghe SR. Development and validation of the Surgical Outcome Risk Tool (SORT). *Br J Surg.* 2014;101(13):1774-1783. doi:10.1002/bjs.9638
35. Donati A, Ruzzi M, Adrario E, et al. A new and feasible model for predicting operative risk. *Br J Anaesth.* 2004;93(3):393-399. doi:10.1093/bja/aeh210
36. Tøttrup A, Erichsen R, Sværke C, Laurberg S, Srensen HT. Thirty-day mortality after elective and emergency total colectomy in Danish patients with inflammatory bowel disease: a population-based nationwide cohort study. *BMJ Open.* 2012;2:1-8. doi:10.1136/bmjopen-2012-000823
37. Mallol M, Sabaté A, Dalmau A, Koo M. Risk factors and mortality after elective and emergent laparatomies for oncological procedures in 899 patients in the intensive care unit: a retrospective observational cohort study. *Patient Saf Surg.* 2013;7(1):29. doi:10.1186/1754-9493-7-29
38. Ingraham AM, Haas B, Cohen ME, Ko CY, Nathens AB. Comparison of Hospital Performance in Trauma vs Emergency and Elective General Surgery. *Arch Surg.* 2012;147(7):591-598. doi:10.1001/archsurg.2012.71
39. Braz LG, Módolo NSP, Nascimento P, et al. Perioperative cardiac arrest: A study of 53 718 anaesthetics over 9 yr from a Brazilian teaching hospital. *Br J Anaesth.* 2006;96(5):569-575. doi:10.1093/bja/ael065
40. Stahlschmidt A, Novelo B, Stefani L. Preditores de mortalidade intra-hospitalar em pacientes submetidos a cirurgias não eletivas. 2017.Trabalho de Conclusão de Residência Médica em Anestesiologia.
41. The Royal College of Surgeons of England. *Emergency Surgery- Standards for Unscheduled Surgical Care.*; 2011. doi:10.1097/00000658-192607000-00017
42. Lee TH, Marcantonio ER, Mangione CM, et al. Derivation and Prospective Validation of a Simple Index for Prediction of Cardiac Risk of Major Noncardiac Surgery. *Circulation.* 1999;100(10):1043 LP - 1049. doi:10.1161/01.CIR.100.10.1043
43. Sutton R, Bann S, Brooks M, Sarin S. The Surgical Risk Scale as an improved tool for risk-adjusted analysis in comparative surgical audit. *Br J Surg.* 2002;89:763-768. doi:10.1046/j.1365-2168.2002.02080.x
44. Bainbridge D, Martin J, Arango M, Cheng D, Outcomes EPC. Perioperative and anaesthetic-related mortality in developed and developing countries: a systematic review and meta-analysis. *Lancet.* 2012;380:1075-1081.doi: 10.1016/S0140-6736(12)60990-8

45. Visser BC, Keegan H, Martin M, Wren SM. Death after colectomy: it's later than we think. *Arch Surg.* 2009;144(11):1021-1027. doi:10.1001/archsurg.2009.197
46. Shah N, Hamilton M. Clinical review: Can we predict which patients are at risk of complications following surgery? *Crit Care.* 2013;17(3):226. doi:10.1186/cc11904
47. Dindo D, Demartines N, Clavien P-A. Classification of surgical complications. *Ann Surg.* 2004;240(2):205-213. doi:10.17116/hirurgia2018090162
48. Bennett-Guerrero E, Welsby I, Dunn TJ, et al. The use of a postoperative morbidity survey to evaluate patients with prolonged hospitalization after routine, moderate-risk, elective surgery. *Anesth Analg.* 1999;89(2):514-519. doi:10.1213/00000539-199908000-00050
49. Grocott MPW, Browne JP, Van der Meulen J, et al. The Postoperative Morbidity Survey was validated and used to describe morbidity after major surgery. *J Clin Epidemiol.* 2007;60(9):919-928. doi:10.1016/j.jclinepi.2006.12.003
50. Story DA, Leslie K, Myles PS, et al. Complications and mortality in older surgical patients in Australia and New Zealand (the REASON study): a multicentre, prospective, observational study. *Anaesthesia.* 2010;65(10):1022-1030. doi:10.1111/j.1365-2044.2010.06478.x
51. Tym MKP, Ludbrook GL, Flabouris A, Seglenieks R, Painter TW. Developing models to predict early postoperative patient deterioration and adverse events. *2017;87:457-461.* doi:10.1111/ans.13874
52. Ghaferi AA, Birkmeyer JD, Dimick JB. Complications, Failure to Rescue, and Mortality With Major Inpatient Surgery in Medicare Patients. *Ann Surg.* 2009;250(6):1029-1034. doi:10.1097/SLA.0b013e3181bef697
53. Boehm O, Baumgarten G, Hoeft A. Epidemiology of the high-risk population : perioperative risk and mortality after surgery. *Curr Opin Crit Care.* 2015;21(4):322-327. doi:10.1097/MCC.0000000000000221
54. Blanch L, Abillama FF, Amin P, et al. Triage decisions for ICU admission: Report from the Task Force of the World Federation of Societies of Intensive and Critical Care Medicine. *J Crit Care.* 2016;36:301-305. doi:10.1016/j.jcrc.2016.06.014
55. Sobol JB, Wunsch H. Triage of high-risk surgical patients for intensive care. *Crit Care.* 2011;15(217):1-7. doi:10.1186/cc9999
56. Kahan BC, Koulenti D, Arvaniti K, et al. Critical care admission following elective surgery was not associated with survival benefit: prospective analysis of data from 27 countries. *Intensive Care Med.* 2017;43(7):971-979. doi:10.1007/s00134-016-4633-8
57. Older P, Hall A. Clinical review: How to identify high-risk surgical patients. *Crit Care.* 2004;8:369-372. doi:10.1186/cc2848
58. Oliver CM, Walker E, Giannaris S, Grocott MPW, Moonesinghe SR. Risk assessment tools validated for patients undergoing emergency laparotomy: a systematic review. *Br J Anaesth.* 2015;115(6):849-860. doi:10.1093/bja/aev350

59. Moonesinghe, S R; Mythen, M; Das P et al. Risk Stratification Tools for Predicting Morbidity and Mortality in Adult Patients Undergoing Major Surgery Qualitative Systematic Review. *Anesthesiology*. 2013;119(4):959-981.
60. Steyerberg EW, Vickers AJ, Cook NR, et al. Assessing the performance of prediction models: a framework for some traditional and novel measures. *Epidemiology*. 2013;21(1):128-138. doi:10.1093/A:1005723304911
61. Cook NR. Use and misuse of the receiver operating characteristic curve in risk prediction. *Circulation*. 2007;115(7):928-935. doi:10.1161/CIRCULATIONAHA.106.672402
62. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): The TRIPOD Statement. *BMJ Open*. 2015;1-9. doi:10.1016/j.eururo.2014.11.025
63. Cook NR. Statistical evaluation of prognostic versus diagnostic models: Beyond the ROC curve. *Clin Chem*. 2008;54(1):17-23. doi:10.1373/clinchem.2007.096529
64. Wijeysundera DN. Precise mathematics yet hazy predictions: Can validated risk indices help improve patient selection for major elective surgery ? *Can J Anesth Can d'anesthésie*. 2017;64(9):893-898. doi:10.1007/s12630-017-0910-4
65. Copeland GP, Jones D, Walters M. POSSUM: a scoring system for surgical audit. *Br J Surg*. 1991;78:356-360.doi:10.1002/bjs.1800780327
66. Brooks MJ, Sutton R, Sarin S. Comparison of Surgical Risk Score, POSSUM and p-POSSUM in higher-risk surgical patients. *Br J Surg*. 2005;92(10):1288-1292. doi:10.1002/bjs.5058
67. Bilmoria, K; Liu, Y; Paruch J; et al. Development and Evaluation of the Universal ACS NSQIP Surgical Risk Calculator: A Decision Aide and Informed Consent Tool for Patients and Surgeons. *J Am Coll Surg*. 2013;217(5):833-842. doi:10.1016/j.jamcollsurg.2013.07.385
68. Marufu TC, White SM, Griffiths R, Moonesinghe SR, Moppett IK. Prediction of 30-day mortality after hip fracture surgery by the Nottingham Hip Fracture Score and the Surgical Outcome Risk Tool. *Anaesthesia*. 2016;71(5):515-521. doi:10.1111/anae.13418
69. Haga Y, Ikejiri K, Wada Y, et al. A multicenter prospective study of surgical audit systems. *Ann Surg*. 2011;253(1):194-201. doi:10.1097/SLA.0b013e3181f66199
70. Boersma E, Kertai MD, Schouten O, et al. Perioperative cardiovascular mortality in noncardiac surgery: Validation of the Lee cardiac risk index. *Am J Med*. 2005;118(10):1134-1141. doi:10.1016/j.amjmed.2005.01.064
71. Quan H, Li B, Couris CM, et al. Updating and Validating the Charlson Comorbidity Index and Score for Risk Adjustment in Hospital Discharge Abstracts Using Data From 6 Countries. *Am J Epidemiol*. 2011;173(6):676-682. doi:10.1093/aje/kwq433
72. Ford MK, Beattie WS, Wijeysundera DN. Systematic Review: Prediction of Perioperative Cardiac Complications and Mortality by the Revised Cardiac Risk Index. *Ann Intern Med*. 2010;152:26-35. doi: 10.7326/0003-4819-152-1-

- 201001050-00007.
73. Gupta PK, Gupta H, Sundaram A, et al. Development and validation of a risk calculator for prediction of cardiac risk after surgery. *Circulation*. 2011;124(4):381-387. doi:10.1161/CIRCULATIONAHA.110.015701
  74. Davis C, Tait G, Carroll J, Wijeysundera DN, Beattie WS. The Revised Cardiac Risk Index in the new millennium: A single-centre prospective cohort re-evaluation of the original variables in 9,519 consecutive elective surgical patients. *Can J Anesth*. 2013;60(9):855-863. doi:10.1007/s12630-013-9988-5
  75. VISION Writing Group. Myocardial injury after noncardiac surgery. *Anesthesiology*. 2014;3(120):564-578. doi:10.1097/HCO.0000000000000069
  76. VISION Writing Group. Association of Postoperative High-Sensitivity Troponin Levels With Myocardial Injury and 30-Day Mortality Among Patients Undergoing Noncardiac Surgery. *Jama*. 2017;317(16):1642-1651. doi:10.1001/jama.2017.4360
  77. Duceppe E, Parlow J, MacDonald P, et al. Canadian Cardiovascular Society Guidelines on Perioperative Cardiac Risk Assessment and Management for Patients Who Undergo Noncardiac Surgery. *Can J Cardiol*. 2017;33(1):17-32. doi:10.1016/j.cjca.2016.09.008
  78. Charlson M, Pompei P, Ales K, MacKenzie R. A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation. *J Chron Dis*. 1987;40(5):373-383. doi:10.1016/0021-9681(87)90171-8
  79. Charlson M, Szatrowski, T, Peterson J et al. Validation of a combined comorbidity. *J Clin Epidemiol*. 1994;47(11):1245-1251. doi:10.1016/0895-4356(94)90129-5
  80. Kork F, Balzer F, Krannich A, Weiss B, Wernecke K-D, Spies C. Association of comorbidities with postoperative in-hospital mortality: a retrospective cohort study. *Medicine (Baltimore)*. 2015;94(8):1-8. doi:10.1097/MD.0000000000000576

## **7 ARTIGOS EM INGLÊS**

7.1 ARTIGO 1 - DERIVATION AND VALIDATION OF A PREOPERATIVE RISK MODEL FOR POSTOPERATIVE MORTALITY (SAMPE MODEL): AN APPROACH TO CARE STRATIFICATION

Artigo 1: artigo publicado na revista PLOS ONE.

## RESEARCH ARTICLE

# Derivation and validation of a preoperative risk model for postoperative mortality (SAMPE model): An approach to care stratification

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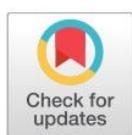
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## OPEN ACCESS

**Citation:** Stefani LC, Gutierrez CDS, Castro SMdJ, Zimmer RL, Diehl FP, Meyer LE, et al. (2017) Derivation and validation of a preoperative risk model for postoperative mortality (SAMPE model): An approach to care stratification. PLoS ONE 12(10): e0187122. <https://doi.org/10.1371/journal.pone.0187122>

**Editor:** Jonathan H. Sherman, George Washington University, UNITED STATES

**Received:** July 5, 2017

**Accepted:** October 13, 2017

**Published:** October 30, 2017

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**Data Availability Statement:** All relevant data are within the paper and its Supporting Information files.

**Funding:** This work was supported by the Fundo de Incentivo à Pesquisa do Hospital de Clínicas de Porto Alegre (FIPe-HCPA- Project 14-0323). The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

## Abstract

Ascertaining which patients are at highest risk of poor postoperative outcomes could improve care and enhance safety. This study aimed to construct and validate a propensity index for 30-day postoperative mortality. A retrospective cohort study was conducted at Hospital de Clínicas de Porto Alegre, Brazil, over a period of 3 years. A dataset of 13524 patients was used to develop the model and another dataset of 7254 was used to validate it. The primary outcome was 30-day in-hospital mortality. Overall mortality in the development dataset was 2.31% [n = 311; 95% confidence interval: 2.06–2.56%]. Four variables were significantly associated with outcome: age, ASA class, nature of surgery (urgent/emergency vs elective), and surgical severity (major/intermediate/minor). The index with this set of variables to predict mortality in the validation sample (n = 7253) gave an AUROC = 0.9137, 85.2% sensitivity, and 81.7% specificity. This sensitivity cut-off yielded four classes of death probability: class I, <2%; class II, 2–5%; class III, 5–10%; class IV, >10%. Model application showed that, amongst patients in risk class IV, the odds of death were approximately fivefold higher (odds ratio 5.43, 95% confidence interval: 2.82–10.46) in those admitted to intensive care after a period on the regular ward than in those sent to the intensive care unit directly after surgery. The SAMPE (Anaesthesia and Perioperative Medicine Service) model accurately predicted 30-day postoperative mortality. This model allows identification of high-risk patients and could be used as a practical tool for care stratification and rational postoperative allocation of critical care resources.

**Competing interests:** The authors have declared that no competing interests exist.

## Introduction

Perioperative risk is multifactorial. It depends on the interaction between anaesthetic, surgical, and patient-specific aspects. The perioperative period can be particularly hazardous to patients because it involves several transfers of care [1,2]. Such fragmentation and discontinuity of care might lead to a system-wide fragility that compromises patient safety, especially in high-risk cases[3]. To mitigate this, patients at heightened risk of poor outcomes should be as visible as possible; labelling them as such throughout their hospitalization could improve the process and safety of care as a whole, including human resources and technical-administrative aspects. Furthermore, in the context of limited health care resources, utilization of critical care resources in the postoperative period is amongst the costliest components of care. This gives rise to several questions: for whom should such specialized care be provided? How can this selection process be made clearer in increasingly crowded and complex health systems?

In recent years, risk management has become a key institutional goal centred on the quality of care, and many surgical risk models and scores have been developed[4]. The ideal stratification tool should be constructed with easily collected preoperative variables that reflect both patient health status and the risk inherent to the surgical procedure. Loss of physiological reserve should also be recognized as a predictor of perioperative vulnerability, and it is essential that the broader characteristics of the patient population of interest be taken into account. The Surgical Risk Scale[5] and de Surgical Mortality Probability model [6] are the proposed indices that come closest to achieving these goals; however, they do not include age as an explanatory variable.

The aim of the present study was to develop a practical approach for stratification of patients undergoing elective or emergent procedures, with satisfactory accuracy, and using feasible, independent preoperative variables. This model would classify patients into risk groups to predict the level of postoperative care required, specifically by making the high-surgical risk group more visible.

## Materials and methods

### Data source and study population

This study was conducted at Hospital de Clínicas de Porto Alegre (HCPA), an 842-bed teaching hospital and referral centre that provides tertiary and quaternary care to patients from across Southern Brazil through the national Unified Health System. Ethical approval for this study was provided by the Ethical Committee of Postgraduate and Research Group from Hospital de Clínicas de Porto Alegre–Brazil (Chairperson Prof. Eduardo P Passos) on the 13<sup>th</sup> of June 2014 (CAAE 30776914.1.0000.5327).

Written informed consent was not required, but the authors signed a confidentiality agreement to assess information from institution's database.

We analysed data from all consecutive surgeries performed from January 1, 2012 to December 31, 2013. We first identified 40,505 records from patients who underwent any form of surgery. We excluded those who received only local anaesthesia by the surgeon or whose procedures were diagnostic rather than therapeutic (26,981). Also when more than one surgical procedure was performed during the same hospital admission, only the major procedure was taken into account for analysis. The final study cohort consisted of 13,524 patients. The database included information on patient demographics, functional status (ASA Physical Status classification), nature of surgery (emergency or elective), and degree of surgery (major, intermediate, or minor; detailed definition provided below), as well as postoperative allocation, e.g.,

regular ward versus intensive care unit. The final outcome during hospitalization was death or survival at hospital discharge. Therefore, the data of the patients who were still in hospital after 30 days or who were discharged before the study period were not followed beyond this point.

### Model development

We used a subsequent approach to select the variables and refine the risk model for surgical mortality. Firstly, only preoperative clinical and surgical routinely available variables with proven accuracy in existing perioperative risk models [5,6] were used. The surgical variables selected were the degree (major, intermediate, or minor) and nature (elective or non-elective) of the procedure. To define surgical severity, we grouped 1200 current terminology codes for similar procedures into subtypes (e.g., bile duct surgery, pulmonary resection). Then, we classified these procedures into major, intermediate, or minor degree, using a categorization scheme based on literature review [6,7] and expert opinions, who considered surgical time, trauma, and predicted bleeding. ([S1 Table](#)). The nature of the procedures was categorized as elective or non-elective (urgent and emergency cases).

Variables related to patient physiological reserve included age and ASA Physical Status (ASA-PS) score. As this model was constructed on the basis of institutional data, other clinical predictors, such as cardiac comorbidities, could not be recovered.

A logistic regression model was adjusted to these four independent predictors: two patient-related (ASA-PS, age) and two procedure-related (surgical severity and elective vs non-elective nature). As noted above, death or survival at hospital discharge was the main outcome of interest. Patients were assessed for up to 30 days of hospitalization.

Odds ratio and 95% confidence intervals were calculated to determine the magnitude with which these variables were associated with likelihood of 30-day in-hospital postsurgical deaths. The C-statistic was used to predict the model's ability to sort patients by outcome. The Hosmer–Lemeshow test was used to check for goodness of fit by comparing the expected and actual deaths in each risk group.

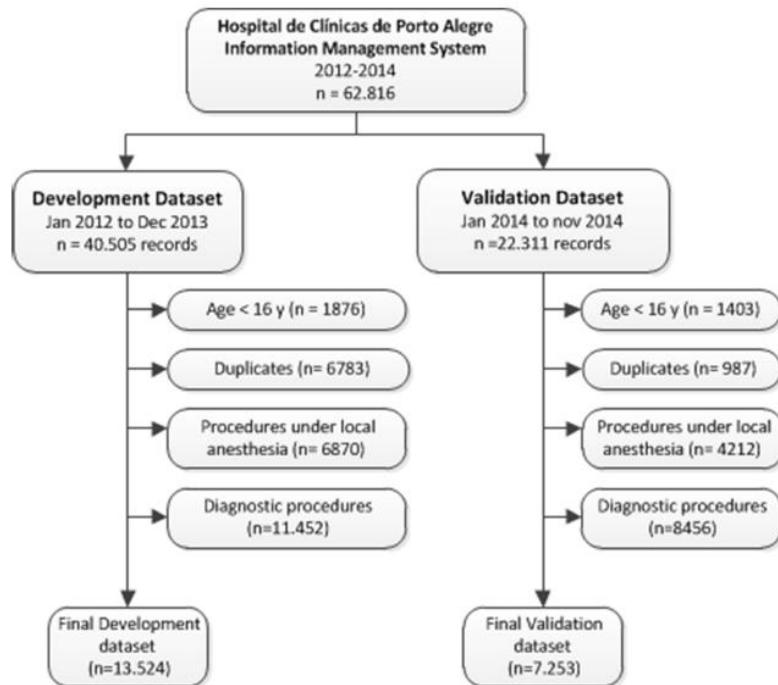
The final model was validated with a new sample (another database from the same institution). The validation dataset was composed of consecutive patients who underwent surgical procedures at the study institution from January to November 2014. The same tests [logistic regression analysis, Hosmer–Lemeshow statistic, receiver operator characteristic (ROC) curve analysis] were applied, using the original sample cut-off point, to confirm the accuracy and calibration of the risk model. All statistical analyses were carried out in the SAS version 9.4.

## Results

### Model development

[Fig 1](#) shows the study flow chart. During the 24 months of analysis, 13524 patients comprised the dataset used to develop the model. In this series, there were 311 operative deaths [2.30%; 95% confidence interval (CI): 2.06–2.56%]. [Table 1](#) describes the characteristics of the overall sample and of the 30-day in-hospital postsurgical deaths, stratified by the clinical and surgical variables of interest. The procedures most frequently associated with 30-day in-hospital mortality are listed in [S2 Table](#). Exploratory laparotomy was the procedure most significantly associated with in-hospital postoperative death.

On adjusted logistic regression analysis, the pre-selected variables age, ASA, nature of procedure (elective vs non-elective), and procedure degree (major, intermediate, or minor) were found to correlate significantly with the final outcome. Each of these variables contributed to mortality. The probability for mortality is showed by the formula (where Y = 1 if the patient



**Fig 1.** Trial diagram for SAMPE model dataset analysis.

<https://doi.org/10.1371/journal.pone.0187122.g001>

died,  $x_1 = \text{age}$ ,  $x_2 = \text{ASA}$ ,  $x_3 = \text{nature}$  and  $x_4 = \text{severity}$ ):

$$P(\text{mortality}) = \log \frac{P(Y = 1|x_1, x_2, x_3, x_4)}{1 - P(Y = 1|x_1, x_2, x_3, x_4)} = -10,7506 + 0,0339 \times \text{age} + 1,7073 \times \text{ASA} + 1,0672 \times \text{nature} - 0,3699 \times \text{intermediate severity} + 0,8966 \times \text{major severity}$$

Tests for linearity were performed for ASA status ( $p = 1.0$ ) and age ( $p = 0.15$ ) by quartiles test and binned residual plot [8] and it suggested that the linearity supposition was accorded, with increments of 1 year for age and one class for ASA status.

Table 2 lists the variables entered into the model and their respective weights (odds ratios and confidence intervals).

By analysing these odds ratios with a view to clinical applicability, we drew several conclusions for each of the variables included in the model. Each 1-year increase in patient age was associated with a 1.35-fold increase in the odds of death. Major (vs minor) surgery was associated with a 2.45-fold increase in the odds of death, while each increment in ASA class led to a 5.51-fold increase. Urgent or emergency surgery increased the odds of death by 2.9 compared to elective surgery.

The accuracy of the final logistic regression model was assessed by its discriminant capacity and calibration. The C-statistic for prediction of in-hospital mortality in the derivation cohort was 0.9137, indicating excellent discrimination. The Hosmer–Lemeshow goodness-of-fit statistic of 13.28 ( $p = 0.125$ ) in the derivation dataset reflects acceptable model calibration.

**Table 1.** Characteristics of the overall sample and 30-day in-hospital postsurgical deaths, stratified by clinical and surgical predictors.

	Total sample		Deaths	
	n	Overall %	n	postoperative deaths %
	13524	100	311	2.30
<b>Age</b>				
15–35	2841	21.00	16	5.14
36–55	4672	34.54	47	15.11
56–75	4901	36.23	161	51.76
>75	1110	8.20	87	27.97
<b>ASA physical status</b>				
I	3349	24.76	2	0.64
II	7439	55.00	58	18.64
III	2466	18.23	149	47.90
IV	247	1.82	82	26.36
V	23	0.17	20	6.43
<b>Nature of procedure</b>				
Elective	10789	79.77	135	43.40
Urgent	2735	20.22	176	56.59
<b>Severity of procedure</b>				
Minor	4809	35.55	50	16.07
Moderate	5593	41.34	66	20.25
Major	3122	23.08	195	62.70

<https://doi.org/10.1371/journal.pone.0187122.t001>

A sensitivity of 85.2% and specificity of 81.7% were obtained for the adjusted model, considering a cut-off value of 0.02 for the predictive probability of death. Full sensitivity and specificity data are provided in [S3 Table](#).

Moreover, the proposed model was compared with a model where the ASA-PS classification was the only predictor, and it added a significant incremental increase in the area under the receiver operating characteristic (AUROC) curve, from 0.857 to 0.913 ( $p < 0.0001$ ) ([Fig 2](#)).

The cut-off sensitivity limit mentioned above yielded four classes of postoperative in-hospital all-cause mortality risk:

Class I—probability of death:  $<2\%$ ;

Class II—probability of death: between 2 and 5% ( $2\% \leq p < 5\%$ );

Class III—probability of death: between 5 and 10% ( $5\% \leq p < 10\%$ );

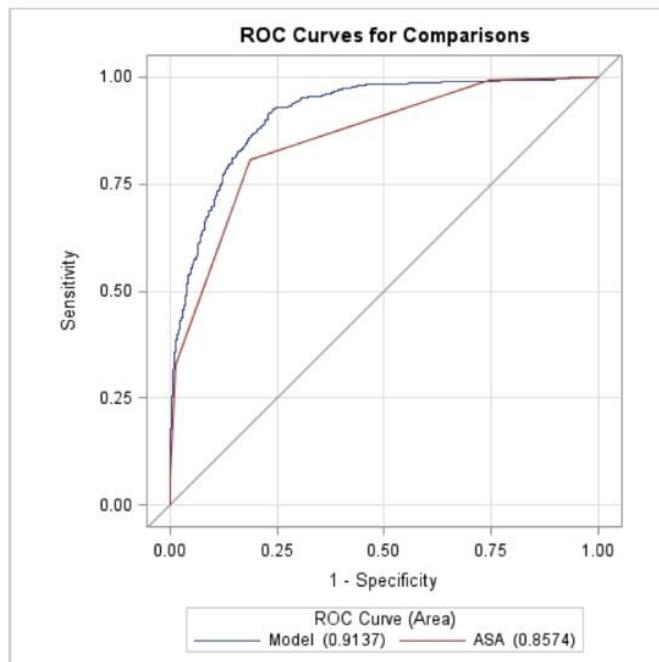
Class IV—probability of death:  $\geq 10\%$ .

**Table 2.** Variables included in the model with respective odds ratios and confidence intervals.

Variable	Odds ratio	95% confidence interval	p
Age	1.035	1.025–1.044	< 0.0001
ASA class	5.514	4.573–6.648	< 0.0001
Surgical severity, intermediate vs minor	0.691	0.467–1.022	0.0641
Surgical severity, major vs minor	2.451	1.750–3.434	< 0.0001
Status, non-elective vs elective	2.907	2.239–3.776	< 0.0001

p-values denote the significance of each variable in improving model predictive capacity (likelihood ratio test).

<https://doi.org/10.1371/journal.pone.0187122.t002>



**Fig 2.** ROC curve calculated using the development SAMPE model dataset compared to the ASA model.

<https://doi.org/10.1371/journal.pone.0187122.g002>

Comparisons of the observed and predicted mortality rates for each class (Table 3) were indicative of model consistency and very good calibration, confirming the results of goodness-of-fit testing [9].

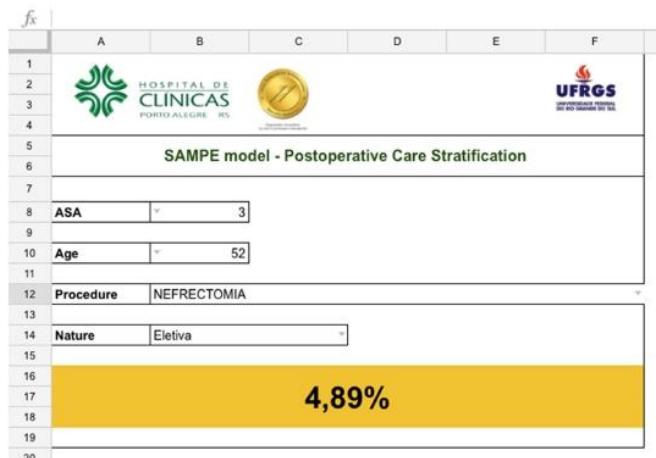
### Model validation and utilization

The discriminant ability and calibration of the final model were then assessed in another validation cohort from the same institution, composed of 7253 patients. The high sensitivity (86.4%) and specificity (81.4%) obtained for prediction of in-hospital mortality at a cut-off value of 0.02 confirmed the accuracy of the final model, which we named “SAMPE”, after our institutional affiliation (*Serviço de Anestesia e Medicina Perioperatória*, Anaesthesia and Perioperative Medicine Service). The C statistic for the validation dataset was 0.922. Also, the calculation of the Hosmer–Lemeshow goodness-of-fit statistic for each decile of risk showed a good concordance between observed and predicted deaths at 30 days ( $\chi^2$  test = 4.27 – p = 0.89).

**Table 3.** Patient mortality in the derivation cohort, stratified by risk class according to the SAMPE model.

Risk class (Predicted mortality)	Total (n = 13.524)	Deaths (%) (n = 311)
Class I—probability of death: <2%;	10.161	28 (0.28)
Class II—probability of death: between 2 and 5%	1.503	49 (3.26)
Class III—probability of death: between 5 and 10%	915	76 (8.31)
Class IV—probability of death: ≥10%	944	158 (16.74)

<https://doi.org/10.1371/journal.pone.0187122.t003>



**Fig 3. Model calculator developed in the Google Docs platform.**

<https://doi.org/10.1371/journal.pone.0187122.g003>

In-hospital death probability was calculated and tabulated for all possible combinations of variables predicted into the model. We also developed an automated on-line table as shown in Fig 3, that calculates the predicted probability of death for each possible combination of variables. This tool will be used to overcome what would otherwise be a considerable challenge—performing a calculation based on a logistic regression equation at the patient's bedside. The calculator is available at <https://www.hcpa.edu.br/downloads/pesquisa/sampe.xlsx>.

Although developed as a risk prediction tool before surgery, the SAMPE model, as any other risk model, should ideally be adjusted for use in a new population.

### Worked example for prediction of intensive care unit admission

To illustrate application of the final model, we evaluated postoperative allocation according to SAMPE risk status. The role of intensive care in the management of high-risk surgical patients was analysed. First, surgical admissions to intensive care units were stratified into two groups: patients transferred directly from the operating theatre to the ICU versus patients transferred to ICU after a period of care in the post-anaesthesia recovery room or on a regular ward. A logistic regression model for mortality was done only on the very high risk patients (class IV), considering the predictors used in the original model plus early or late ICU admission (Table 4). Overall, 944 patients were classified as having very high surgical risk ( $\geq 10\%$  mortality, i.e., SAMPE class IV). Of these patients, 158 (17%) died. The mortality odds ratio from patients admitted late versus early in ICU was 5.431 (IC 2.820–10.462). The remained patients that died in this category (risk class IV) were not admitted at any time in the intensive care unit (47 patients).

### Discussion

Statistical risk models for prediction of mortality can be seen as adjuncts to diagnosis, and are best used to enhance perioperative risk reduction strategies. The greatest challenges are to incorporate the chosen model into the care process and ascertain its impact on postoperative outcomes. In this study, we used a dataset of 13524 patients to construct a preoperative model based on clinical and surgical variables, to stratify adult patients into risk classes of in-hospital mortality probability for general surgery. After adjustment and refinement, we validated the

**Table 4. Mortality-adjusted logistic regression model parameters for high-risk patients (n = 944) and their odds ratio estimates for each predictor.**

Predictors	Beta	Standard error	OR	95% CI
<b>Age</b>	0.055	0.01	1.057	1.03–1.07
<b>ASA</b>	1.757	0.210	5.8	3.83–8.76
<b>Surgical Severity</b>				
Low	Ref	-	-	-
Intermediate	-0.177	0.428	0.838	0.36–1.94
Major	0.416	0.367	1.517	0.73–3.11
<b>Nature</b>				
Elective	Ref	-	-	-
Urgent/Emergent	1.322	0.295	3.753	2.10–6.69
<b>ICU admission</b>				
Early ICU	Ref	-	-	-
No ICU admission	1.454	0.24	0.23	0.14–0.37
Late ICU	3.146	0.327	5.431	2.82–10.46

<https://doi.org/10.1371/journal.pone.0187122.t004>

model on 7253 patients with a high degree of accuracy. The main strength of our model is that we translate the mathematical model into an automated on-line table that informs the risk and divides it into four categories. This approach creates an efficient risk communication system to the collaborative teams, being its two main goals to predict postoperative complications and to prevent the failure to rescue.

It has already been demonstrated that postoperative death rates oscillate widely across hospitals, even if they have similar complication rates. The hospitals with the best results invest their efforts in the ability of effectively rescue a patient from a complication once it occurs: from timely recognition to effective management[10]. Ferraris et al [11] showed that 20% of patients with the greatest risk for developing postoperative complications account for 90% of failure to rescue. Therefore, identifying these high-risk patients and implementing timely recognition and treatment of early complications are the best opportunity to intervene and limit failure to rescue.

### The model

The high performance of the SAMPE model in the validation cohort (AUROC = 0.913) confirms its consistency. Unfortunately, all risk models currently in use have limitations. Some employ the same variables we selected[5–7] but have limited generalizability and are not easily applied at the bedside. Others, such as the POSSUM score, rely on multiple pre and intraoperative variables and have been shown to overestimate mortality in lower-risk groups [12,13].

One of the strengths of our model is the absence of multiple variables or excessive analyses, which could result in overfitting. Another advantage is its applicability at bedside where it can be used preoperatively, without intraoperative data or laboratory results.

The few clinical and surgical variables selected were powerful predictors of the outcome of interest. Therefore, if a pre-selected combination of variables can explain a phenomenon with the same level of accuracy as a more complex model, the former should be preferred; according to the law of parsimony[14].

It's known that the models considering surgical and clinical variables have greater accuracy. The comparison of some mortality models using only preoperative variables is shown in Table 5.

**Table 5. Mortality models with pre-operative variables.**

Model	Variables included in the model	Outcome	Population	AUROC (CI)	Comments
<b>SORT model [15]</b>	ASA, Surgical Nature, High risk specialty, Surgical Severity, Cancer, Age	Predicted risk of 30-day mortality	General non-cardiac surgery (n = 16.788)	0.91 (0.88–0.94)	It's a multicenter study in United Kingdom that used a specific surgical severity classification. ROC curve comparing this model with Surgical Risk Scale and ASA was superior. It needs an app web-base calculator.
<b>Surgical Mortality Probability Model, (SMP-M) [6]</b>	Surgical severity, ASA, Surgical Nature	30 day mortality	General surgical patients, (n = 298.772)	0.89	It's a model based on the American College of Surgeons Program database (ACS NSQIP). It exhibited good discrimination compared to the 35-variable ACS NSQIP risk adjustment model.
<b>mE-PASS [16]</b>	Age, Severe Pulmonary disease, Severe heart disease, Diabetes mellitus, ASA class, Performance status, Surgical Procedures	In-hospital mortality and 30 day mortality	General surgical patient (n = 5.272)	In hospital mortality: 0.86 (0.79–0.92) 30 day mortality: 0.81 (0.66–0.96)	Model derived from the Japanese National Health Care Reimbursement System. Good accuracy compared to models that included intra-operative variables (E-PASS and POSSUM).
<b>Lee Cardiac Risk Index [17]</b>	High risk surgery ( <i>retroperitoneal, intrathoracic, suprainguinal vascular</i> ), ischemic heart disease, heart failure, cerebral vascular disease, renal insufficiency, diabetes mellitus	Cardiac mortality up to 30 days	General non-cardiac surgery, (n = 108.593)	0.63	The outcome is focused on cardiovascular mortality. Its simple classification of procedures as high-risk versus not high-risk seems suboptimal.
<b>Surgical Risk Score[7]</b>	ASA, surgical severity, surgical nature, age	Inpatient mortality	General surgery, (n = 1.849)	0.88 (0.83–0.93)	It was developed and validated in Italy. Subsequent study evaluating this model found it to be poorly predictive of in-patient mortality [16].
<b>ASA PS[7]</b>	ASA	Inpatient mortality	General surgical patient (n = 1.849)	0.81 (0.79–0.82)	ASA grade has been used since 1941. In this cohort, it had good accuracy in predicting mortality even being the only predictor.
<b>Charlson [18]</b>	19 clinical conditions	30 day mortality	General surgery (n = 2.167)	0.52	The index is designed to predict 1-year mortality. It does not consider the surgical procedure. In this cohort, the index was the least able to predict mortality.
<b>Surgical Risk Scale[5]</b>	ASA, surgical severity—( <i>minor, intermediate, major, major plus, complex major</i> ), surgical nature ( <i>elective, scheduled, urgent, emergency</i> )	Inpatient mortality	Gastrointestinal, vascular, trauma (n = 1.946)	0.95 (0.93–0.97)	Incorporates specific subclassifications: the CEDOP (Confidential Enquiry into Perioperative Deaths) grade and BUPA (British United Provident Association) classification. Transformed the multivariate regression in a pragmatic score.

<https://doi.org/10.1371/journal.pone.0187122.t005>

This study has several limitations. First, the model reflects mortality risk in the patient population of the study facility, and cannot yet be generalized to other care settings or geographic locations. Second, although it was designed to provide a relatively accurate assessment, 2 of 4 (ASA and surgical severity) variables are subjective measures.

Third, it is limited by the fact that the data were obtained retrospectively; further work is needed to compare the accuracy of the SAMPE model to that of other risk models in a multi-centre design. Nevertheless, the numbers at our hospital did not differ greatly from rates reported in developed countries. The overall in-hospital mortality of our sample (2.3%) was comparable to the overall mortality in a 7-day European cohort study[19]. The mortality of patients undergoing high-risk procedures, especially laparotomies, was consistent with that

recorded in an ongoing audit project at UK hospitals[20], and the mortality of high-risk patients (8.5%) was similar to that found in a study focused on a similar population [21]. Finally, the outcome in-hospital mortality could bypass the no-less important outcome of perioperative complications, as it is a hard endpoint and postoperative complications are more difficult to define and quantify.

### The variables

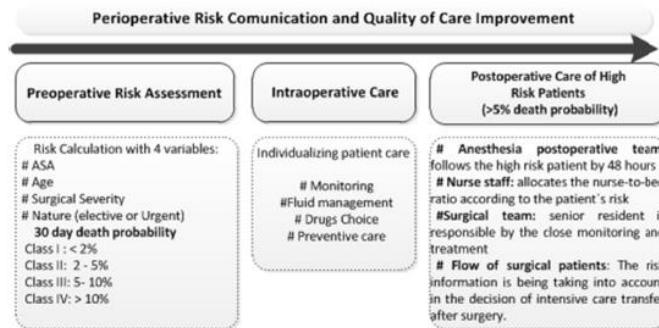
Age has been identified as an important predictor of increased risk of postoperative mortality. However, it is not age itself that leads to heightened risk, but rather the decline in bodily functions that comes with ageing [22]. The impact of age-associated decline in five domains is demonstrated in the recently developed Frailty Score[23,24] which has been associated with higher expectancy of adverse hard end-points following surgery, including mortality, functional decline, and cardiac complications.

The most significant variable in the SAMPE model is the physical condition of the patient, determined by the ASA-PS classification. Despite its classic, widespread use and subjective nature, this score was not originally developed for prediction of adverse outcomes; nevertheless, adequate inter-reliability in clinical practice was recently demonstrated[25]. Furthermore, it reflects the global health status of the patient, irrespective of the body systems affected by current pathology. The ASA classification has also been used as the main clinical variable in several recent perioperative risk models, such as the SPM-P model[6] and the Gupta model [26]. The predictive performance of these models exceeds that of traditional risk indices such as the Cardiac Index Revised[17] and the ACS-NSQIP model[27]. In order to reduce the subjectivity of the ASA classification, it's recommendable the use of the recent update published by the American Society of Anesthesiologists, which encompasses ASA-approved class-specific examples belonging to each class (<http://www.asahq.org/resources/clinical-information/asa-physical-status-classification-system>).

The risk inherent to the type of procedure performed is also of utmost importance. Elective and less complex procedures had the lowest rates of postoperative mortality, while the worst outcomes were found in patients undergoing major procedures. In our study, only the comparison between major versus minor surgeries was significantly predictive in the model. The classification of procedural severity was adapted from the SPM-P model[6] and corrected for local context after consultation with experts from various surgical specialties and analysis of crude procedure-related mortality, since it depends on several factors related to the whole continuum of perioperative care. The electronic tool contains all procedures previously classified by its severity, which reduces inter-user variability.

Non-elective surgery is a recognized risk factor for perioperative mortality, especially in abdominal procedures[28]. In emergent surgery, there is limited time for data collection and preoperative optimization of comorbid states[29]. Furthermore, the lack of structured care in the crowded and hectic setting of the emergency department certainly contributes to insufficient patient preparation and poor definition of the goals of care. It was recently demonstrated in a large English NHS cohort that structural and procedural aspects such as the number of doctors, nurse staffing, available operating rooms, and critical care beds are important modifying factors related to 30- and 90-day post-emergent surgical mortality[30].

In a worked example, we were able to highlight the ability of our model to guide rational utilization of resources, including postoperative intensive-care allocation, through surgical risk stratification. Despite a higher overall mortality rate (16%) and accounting for over 50% of in-hospital deaths, only 29% of very-high risk (class IV) patients in the cohort were admitted to critical care at any time following surgery (204 early admission vs 68 late admission).



**Fig 4. Flow of the high-risk patient's care.**

<https://doi.org/10.1371/journal.pone.0187122.g004>

Perhaps most importantly, we found that late admission to the intensive care unit was associated with increased mortality. The very high-risk patients admitted to intensive care after a period of recovery on a regular ward had a 5.43-fold greater risk of postoperative death compared with those admitted to intensive care directly after surgery. Our results confirm the previous findings of higher mortality amongst high-risk patients that were not immediately admitted to a critical care unit after surgery in a large NHS trust [31]. One explanation for these rates could be the lack of availability of critical care resources, since only 4.7% of all risk class patients had immediate postoperative ICU allocation. This contrasts with a European 7-day cohort in which 8% of patients were admitted to the ICU postoperatively [19].

It's important to emphasize that other determinant variables such as respiratory and haemodynamic instability or trans-operative complications were not included in the pre-operative model. Thus, the model could not be the only source of ICU admission but it may be a useful tool in the allocation decision, especially when there are scarce critical bed resources.

We believe that recognition, identification, and increased visibility of patients with high perioperative risk could make a greater contribution to improving the quality and safety of care than would simply ensuring the availability of critical care resources.

This objective risk assessment could be used to identify which patients must be actively followed in the postoperative period. Multidisciplinary postoperative care teams could also be created, with a view to providing enhanced, patient-centred care and improving postoperative outcomes.

Accordingly, some processes are been encouraged to be implemented by different caregivers after adopting SAMPE risk model adoption during the high-risk patients' hospitalization: (i) The postoperative and acute pain team follows them for 48 hours; (ii) the surgeon team assigns senior residents to care for these patients; (iii) the internal medicine co-management is implemented and optimized; (iv) the nurse staff staggers care by prioritizing high-risk patients, evaluating the vital signs more often than usual, and defining nurse-to-bed ratio according to patient's risk. Additionally, the classification is taken into account in the decision of a possible patient transfer to the ICU after surgery (Fig 4).

## Conclusions

Our perioperative mortality risk model exhibited excellent performance with a small set of easily assessed and sustainable variables. Although the model was well validated internally, prospective validation in external samples is crucial. However, accurate identification of high-risk patients is not enough. The key challenge for clinical translation of our findings, as well as a

major avenue for future research, is to incorporate our risk model as a component of care and ascertain its impact on patient outcomes. If successful, this could contribute to improved patient safety and more efficient utilization of perioperative care resources.

## Supporting information

**S1 Table. Surgical severity criteria developed on the basis of surgical opinion leaders and a literature review, adjusted for crude mortality in the study population.**  
(DOCX)

**S2 Table. Procedures most frequently associated with mortality in the development data-set.**  
(DOCX)

**S3 Table. Sensitivity and specificity of the model.**  
(DOCX)

## Author Contributions

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**Funding acquisition:** Luciana Cadore Stefani.

**Investigation:** Luciana Cadore Stefani, Claudia De Souza Gutierrez.

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**Resources:** Luciana Cadore Stefani.

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**Supervision:** Luciana Cadore Stefani.

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**Visualization:** Luciana Cadore Stefani, Rafael Leal Zimmer.

**Writing – original draft:** Luciana Cadore Stefani, Felipe Polgati Diehl, Leonardo Elman Meyer, Wolnei Caumo.

**Writing – review & editing:** Luciana Cadore Stefani.

## References

1. Birkmeyer JD, Siewers AE, Finlayson EVA, Stukel TA, Lucas FL, Batista I, et al. Hospital Volume and Surgical Mortality in the United States. *N Engl J Med.* 2002; 346: 1128–1137. <https://doi.org/10.1056/NEJMsa012337> PMID: 11948273
2. Ghaferi A a, Birkmeyer JD, Dimick JB. Complications, failure to rescue, and mortality with major inpatient surgery in medicare patients. *Ann Surg.* 2009; 250: 1029–1034. <https://doi.org/10.1097/SLA.0b013e3181bef697> PMID: 19953723
3. Moonesinghe SR, Mythen MG, Grocott MPW. High-risk surgery: Epidemiology and outcomes. *Anesth Analg.* 2011; 112: 891–901. <https://doi.org/10.1213/ANE.0b013e3181e1655b> PMID: 20495138

4. Moonesinghe SR, Mythen MG, Das P, Rowan KM, Grocott MP. Risk stratification tools for predicting morbidity and mortality in adult patients undergoing major surgery: qualitative systematic review. *Anesthesiology*. 2013; 119: 959–981. <https://doi.org/10.1097/ALN.0b013e3182a4e94d> PMID: 24195875
5. Sutton R, Bann S, Brooks M, Sarin S. The Surgical Risk Scale as an improved tool for risk-adjusted analysis in comparative surgical audit. *Br J Surg.* 2002; 89: 763–768. <https://doi.org/10.1046/j.1365-2168.2002.02080.x> PMID: 12027988
6. Glance LG, Lustik SJ, Hannan EL, Osler TM, Mukamel DB, Qian F, et al. The Surgical Mortality Probability Model. *Ann Surg.* 2012; 255: 696–702. <https://doi.org/10.1097/SLA.0b013e31824b45af> PMID: 22418007
7. Donati A., Ruzzi M, Adrario E, Pelaia P, Coluzzi F, Gabbanelli V, et al. A new and feasible model for predicting operative risk. *Br J Anaesth.* 2004; 93: 393–399. <https://doi.org/10.1093/bja/aeh210> PMID: 15220171
8. Collett D. Modelling Survival Data in Medical Research, Third Edition. Texts in statistical science. 2015. 10.1198/tech.2004.s817
9. Kramer A a, Zimmerman JE. Assessing the calibration of mortality benchmarks in critical care: The Hosmer-Lemeshow test revisited. *Crit Care Med.* 2007; 35: 2052–2056. <https://doi.org/10.1097/01.CCM.0000275267.64078.B0> PMID: 17568333
10. Ghaferi AA, Birkmeyer JD, Dimick JB. Variation in Hospital Mortality Associated with Inpatient Surgery. *N Engl J Med.* 2009; 361: 1368–1375. <https://doi.org/10.1056/NEJMsa0903048> PMID: 19797283
11. Ferraris V a, Bolanos M, Martin JT, Mahan A, Saha SP. Identification of Patients With Postoperative Complications Who Are at Risk for Failure to Rescue. *JAMA Surg.* 2014; 149: 1103–1108. <https://doi.org/10.1001/jamasurg.2014.1338> PMID: 25188264
12. Brooks MJ, Sutton R, Sarin S. Comparison of Surgical Risk Score, POSSUM and p-POSSUM in higher-risk surgical patients. *Br J Surg.* 2005; 92: 1288–1292. <https://doi.org/10.1002/bjs.5058> PMID: 15981213
13. Stonelake S, Thomson P, Suggett N. Identification of the high risk emergency surgical patient: Which risk prediction model should be used? *Ann Med Surg.* 2015; 4: 240–247. <https://doi.org/10.1016/j.amsu.2015.07.004> PMID: 26468369
14. Feinstein AR, Wells CK, Walter SD. A comparison of multivariable mathematical methods for predicting survival—I. Introduction, rationale, and general strategy. *J Clin Epidemiol.* 1990; 43: 339–347. [https://doi.org/10.1016/0895-4356\(90\)90120-E](https://doi.org/10.1016/0895-4356(90)90120-E) PMID: 2324775
15. Protopapa KL, Simpson JC, Smith NCE, Moonesinghe SR. Development and validation of the Surgical Outcome Risk Tool (SORT). *Br J Surg.* 2014; 101: 1774–1783. <https://doi.org/10.1002/bjs.9638> PMID: 25388883
16. Haga Y, Ikejiri K, Wada Y, Takahashi T, Ikenaga M, Akiyama N, et al. A multicenter prospective study of surgical audit systems. *Ann Surg.* 2011; 253: 194–201. <https://doi.org/10.1097/SLA.0b013e3181f66199> PMID: 21233616
17. Boersma E, Kertai MD, Schouten O, Bax JJ, Noordzij P, Steyerberg EW, et al. Perioperative cardiovascular mortality in noncardiac surgery: Validation of the Lee cardiac risk index. *Am J Med.* 2005; 118: 1134–1141. <https://doi.org/10.1016/j.amjmed.2005.01.064> PMID: 16194645
18. Atherly A, Fink AS, Campbell DC, Mentzer RM, Henderson W, Khuri S, et al. Evaluating alternative risk-adjustment strategies for surgery. *Am J Surg.* 2004; 188: 566–570. <https://doi.org/10.1016/j.amjsurg.2004.07.032> PMID: 15546571
19. Pearse RM, Moreno RP, Bauer P, Pelosi P, Metnitz P, Spies C, et al. Mortality after surgery in Europe: a 7 day cohort study. *Lancet.* 2012; 380: 1059–1065. [https://doi.org/10.1016/S0140-6736\(12\)61148-9](https://doi.org/10.1016/S0140-6736(12)61148-9) PMID: 22998715
20. Saunders DI, Murray D, Pichel AC, Varley S, Peden CJ. Variations in mortality after emergency laparotomy: The first report of the UK emergency laparotomy network. *Br J Anaesth.* 2012; 109: 368–375. <https://doi.org/10.1093/bja/aes165> PMID: 22728205
21. Jakobson T, Karjagin J, Vipp L, Padar M, Parikh A-H, Starkopf L, et al. Postoperative complications and mortality after major gastrointestinal surgery. *Medicina (Kaunas).* 2014; 50: 111–7. <https://doi.org/10.1016/j.medici.2014.06.002> PMID: 25172605
22. Elsayed H, Whittle I, McShane J, Howes N, Hartley M, Shackcloth M, et al. The influence of age on mortality and survival in patients undergoing oesophagogastrectomies. A seven-year experience in a tertiary centre. *Interact Cardiovasc Thorac Surg.* 2010; 11: 65–9. <https://doi.org/10.1510/icvts.2009.223826> PMID: 20378697
23. Makary M a., Segev DL, Pronovost PJ, Syin D, Bandeen-Roche K, Patel P, et al. Frailty as a Predictor of Surgical Outcomes in Older Patients. *J Am Coll Surg.* Elsevier Inc.; 2010; 210: 901–908. <https://doi.org/10.1016/j.jamcollsurg.2010.01.028> PMID: 20510798

24. Sepehri A, Beggs T, Hassan A, Rigatto C, Shaw-Daigle C, Tangri N, et al. The impact of frailty on outcomes after cardiac surgery: a systematic review. *J Thorac Cardiovasc Surg.* 2014; 148: 3110–7. <https://doi.org/10.1016/j.jtcvs.2014.07.087> PMID: 25199821
25. Sankar A, Johnson SR, Beattie WS, Tait G, Wijeysundera DN. Reliability of the American Society of Anesthesiologists physical status scale in clinical practice. *Br J Anaesth.* 2014; 113: 424–432. <https://doi.org/10.1093/bja/aeu100> PMID: 24727705
26. Gupta PK, Gupta H, Sundaram A, Kaushik M, Fang X, Miller WJ, et al. Development and validation of a risk calculator for prediction of cardiac risk after surgery. *Circulation.* 2011; 124: 381–387. <https://doi.org/10.1161/CIRCULATIONAHA.110.015701> PMID: 21730309
27. Cohen ME, Ko CY, Biliomia KY, Zhou L, Huffman K, Wang X, et al. Optimizing ACS NSQIP modeling for evaluation of surgical quality and risk: Patient risk adjustment, procedure mix adjustment, shrinkage adjustment, and surgical focus. *J Am Coll Surg.* Elsevier Inc; 2013; 217: 336–346.e1. <https://doi.org/10.1016/j.jamcollsurg.2013.02.027> PMID: 23628227
28. Kurian A, Suryadevara S, Ramaraju D, Gallagher S, Hofmann M, Kim S, et al. In-Hospital and 6-month mortality rates after open elective vs open emergent colectomy in patients older than 80 years. *Dis Colon Rectum.* 2011; 54: 467–471. <https://doi.org/10.1007/DCR.0b013e3182060904> PMID: 21383568
29. Merani S, Payne J, Padwal RS, Hudson D, Widder SL, Khadaroo RG. Predictors of in-hospital mortality and complications in very elderly patients undergoing emergency surgery. *World J Emerg Surg.* 2014; 9: 43. <https://doi.org/10.1186/1749-7922-9-43> PMID: 25050133
30. Ozdemir B a., Sinha S, Karthikesalingam a., Poloniecki JD, Pearse RM, Grocott MPW, et al. Mortality of emergency general surgical patients and associations with hospital structures and processes. *Br J Anaesth.* 2016; 116: 54–62. <https://doi.org/10.1093/bja/aev372> PMID: 26675949
31. Jhanji S, Thomas B, Ely A, Watson D, Hinds CJ, Pearse RM. Mortality and utilisation of critical care resources amongst high-risk surgical patients in a large NHS trust. *Anaesthesia.* 2008. pp. 695–700. <https://doi.org/10.1111/j.1365-2044.2008.05560.x> PMID: 18489613

**S1 Table.** Surgical severity criteria developed on the basis of surgical opinion leaders and a literature review, adjusted for crude mortality in the study population.

<b>Surgical severity</b>	<b>Definition</b>	<b>Procedures included</b>
<b>Minor</b>	<p>Minimal or minor risk, independent of clinical conditions or anaesthesia</p> <p>Minimally to moderately invasive procedure</p>	<p>Minor (laparoscopic) gynaecological procedures</p> <p>Breast surgery</p> <p>Minor ENT procedures</p> <p>Minor oral and maxillofacial procedures</p> <p>Uncomplicated hernia repair</p> <p>Appendectomy</p> <p>Minor genitourinary procedures (nephrostomy, cystoscopy, extracorporeal shock-wave lithotripsy, bladder biopsy)</p> <p>Thyroidectomy</p> <p>Laparoscopy</p> <p>Cosmetic plastic surgeries</p> <p>Minor orthopaedic procedures (tendon release, small-joint surgery)</p>

		Haemorrhoidectomy
<b>Moderate</b>	<p>Moderately invasive procedure</p> <p>Potential estimated blood loss 500-1500 ml</p> <p>Moderate risk to patient independent of clinical conditions or anaesthesia</p>	<p>Endovascular aortic aneurysm repair</p> <p>Minor orthopaedic and spinal procedures (laminectomy, anterior and posterior cervical arthrodesis, hip or knee arthroscopy, open reduction of jaw fractures).</p> <p>Cholecystectomy (open or laparoscopic)</p> <p>Ostomy procedures (gastrostomy, ileostomy, colostomy)</p> <p>Minor chest procedures (mediastinoscopy, sympathectomy, tracheal prosthesis, video-assisted thoracoscopic surgery)</p> <p>Oesophageal surgery for benign conditions (pyloromyotomy, oesophagomyotomy, fundoplication)</p> <p>Splenectomy</p> <p>Hysterectomy</p> <p>Minimally invasive or minor neurosurgical procedures (brain biopsy, ventriculoperitoneal shunting, endoscopic intracranial surgery, endoscopic third ventriculostomy)</p>

		Percutaneous or laparoscopic genitourinary tract procedures (nephrectomy, adrenalectomy, pyeloplasty, pyelolithotomy, transurethral resection of the prostate or bladder, laparoscopic radical nephroureterectomy)  Pleural surgery (pleurodesis)
<b>Major</b>	<p>Highly invasive procedure</p> <p>Potential estimated blood loss greater than 1500 ml</p> <p>Major to critical risk to patient independent of clinical conditions or anaesthesia</p>	Any heart surgery  Exploratory laparotomy  Colorectal resections/bowel anastomoses (colectomy, rectosigmoidectomy, abdominoperineal resection)  Oesophageal surgery for malignant conditions (oesophagectomy, oesophagogastrectomy) or diaphragmatic hernia repair  Arterial bypass procedures (femorofemoral, aortofemoral, axillofemoral, embolectomy)  Amputations (above/below-elbow, above/below-knee, upper limb, lower limb)  Open aneurysm repair (abdominal, thoracic, or thoracoabdominal aortic aneurysm, surgical repair of aortic dissection)  Hepatic or biliary tract procedures (hepatectomy, biliary tract exploration, biliary-

	<p>enteric anastomosis)</p> <p>Pancreatectomy</p> <p>Major orthopaedic procedures (spinal arthrodesis, revision arthroplasty)</p> <p>Major chest procedures (lobectomy, pneumonectomy, decortication, exploratory thoracotomy, thymectomy)</p> <p>Major genitourinary tract procedures (radical cystectomy, nephrectomy, radical prostatectomy, Wertheim-Meigs operation, cystenterostomy),</p> <p>Major ENT procedures (laryngectomy, mandibulectomy, tumour resections)</p> <p>Craniotomy for non-vascular conditions (intracranial tumours, hypophysectomy, spinal tumours)</p> <p>Vascular microsurgery, drainage of subdural or intracerebral hematoma</p> <p>Retroperitoneal resections/hemipelvectomy</p>
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**S2 Table.** Procedures most frequently associated with mortality in the development dataset

Procedure	Number of Patients	Deaths	% over total number of deaths (n=314)	
			%	
Laparotomy	430	94	17.73	29.84
Arterial bypass	189	22	11.64	7
Colorectal resection	337	21	6.23	6.68
Gastric resection	289	15	5.19	4.77
Amputation (vascular)	168	15	8.92	4.77
Minor neurosurgery	56	17	30.36	4.45
Ostomy	111	13	11.71	4.14
Vascular neurosurgery	66	10	15.15	3.18
Non-vascular neurosurgery	150	7	4.66	2.23
Bowel anastomosis	72	7	9.72	2.23

**Supplement 3.** Sensitivity and specificity of the model

Classification Table										
Prob.	Correct			Incorrect			Percentages			
	Level	Event	Non-Event	Event	Non-Event	Correct	Sensitivity	Specificity	False POS	False NEG
0.000	311	0	13213	0	2.3	100.0	0.0	97.7	.	.
0.020	270	10548	2665	41	80.0	86.8	79.8	90.8	0.4	.
0.040	234	11555	1658	77	87.2	75.2	87.5	87.6	0.7	.
0.060	198	11993	1220	113	90.1	63.7	90.8	86.0	0.9	.
0.080	177	12290	923	134	92.2	56.9	93.0	83.9	1.1	.
0.100	151	12517	696	160	93.7	48.6	94.7	82.2	1.3	.
0.120	129	12693	520	182	94.8	41.5	96.1	80.1	1.4	.
0.140	113	12801	412	198	95.5	36.3	96.9	78.5	1.5	.
0.160	100	12863	350	211	95.9	32.2	97.4	77.8	1.6	.
0.180	92	12933	280	219	96.3	29.6	97.9	75.3	1.7	.
0.200	85	12978	235	226	96.6	27.3	98.2	73.4	1.7	.
0.220	80	13024	189	231	96.9	25.7	98.6	70.3	1.7	.
0.240	71	13060	153	240	97.1	22.8	98.8	68.3	1.8	.
0.260	69	13092	121	242	97.3	22.2	99.1	63.7	1.8	.
0.280	57	13128	85	254	97.5	18.3	99.4	59.9	1.9	.
0.300	51	13146	67	260	97.6	16.4	99.5	56.8	1.9	.

**Classification Table**

Prob.	Correct		Incorrect		Percentages					
	Level	Event	Non-Event	Event	Non-Event	Correct	Sensitivity	Specificity	False POS	False NEG
0.320		45	13152	61	266	97.6	14.5	99.5	57.5	2.0
0.340		38	13171	42	273	97.7	12.2	99.7	52.5	2.0
0.360		34	13177	36	277	97.7	10.9	99.7	51.4	2.1
0.380		19	13187	26	292	97.6	6.1	99.8	57.8	2.2
0.400		17	13197	16	294	97.7	5.5	99.9	48.5	2.2
0.420		11	13204	9	300	97.7	3.5	99.9	45.0	2.2
0.440		5	13207	6	306	97.7	1.6	100.0	54.5	2.3
0.460		3	13212	1	308	97.7	1.0	100.0	25.0	2.3
0.480		1	13213	0	310	97.7	0.3	100.0	0.0	2.3
0.500		0	13213	0	311	97.7	0.0	100.0	.	2.3

**TRIPOD Checklist: Prediction Model Development and Validation**

Section/Topic	Item	Checklist Item			Page
<b>Title and abstract</b>					
Title	1	D;V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.		1
Abstract	2	D;V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.		1
<b>Introduction</b>					
Background and objectives	3a	D;V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.		2
	3b	D;V	Specify the objectives, including whether the study describes the development or validation of the model or both.		2
<b>Methods</b>					
Source of data	4a	D;V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.		2
	4b	D;V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.		2
Participants	5a	D;V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.		2
	5b	D;V	Describe eligibility criteria for participants.		2-3
	5c	D;V	Give details of treatments received, if relevant.		NA
Outcome	6a	D;V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.		2-3
	6b	D;V	Report any actions to blind assessment of the outcome to be predicted.		NA
Predictors	7a	D;V	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.		3
	7b	D;V	Report any actions to blind assessment of predictors for the outcome and other predictors.		NA
Sample size	8	D;V	Explain how the study size was arrived at.		NA
Missing data	9	D;V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.		NA
Statistical analysis methods	10a	D	Describe how predictors were handled in the analyses.		3
	10b	D	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.		3-6
	10c	V	For validation, describe how the predictions were calculated.		3-6
	10d	D;V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.		3-6
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.		NA
Risk groups	11	D;V	Provide details on how risk groups were created, if done.		NA
Development vs. validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.		6
<b>Results</b>					
Participants	13a	D;V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.		4
	13b	D;V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.		5
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).		NA
Model development	14a	D	Specify the number of participants and outcome events in each analysis.		4-5
	14b	D	If done, report the unadjusted association between each candidate predictor and outcome.		NA
Model specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).		4
	15b	D	Explain how to use the prediction model.		6-7
Model performance	16	D;V	Report performance measures (with CIs) for the prediction model.		4-6
Model-updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).		NA
<b>Discussion</b>					
Limitations	18	D;V	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).		9-10
Interpretation	19a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.		NA
	19b	D;V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.		7-10
Implications	20	D;V	Discuss the potential clinical use of the model and implications for future research.		11
<b>Other information</b>					
Supplementary information	21	D;V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.		12
Funding	22	D;V	Give the source of funding and the role of the funders for the present study.		12

\*Items relevant only to the development of a prediction model are denoted by D, items relating solely to a validation of a prediction model are denoted by V, and items relating to both are denoted D;V. We recommend using the TRIPOD Checklist in conjunction with the TRIPOD Explanation and Elaboration document.

7.2 ARTIGO 2 - THE ACCURACY OF THE SAMPE RISK MODEL FOR  
POSTOPERATIVE IN-HOSPITAL MORTALITY PREDICTION COMPARED TO  
THE REVISED CARDIAC RISK AND CHARLSON COMORBIDITY INDEXES

## Title Page

**Title:** The accuracy of the SAMPE risk model for postoperative in-hospital mortality prediction compared to the Revised Cardiac Risk and Charlson Comorbidity Indexes

**Running title:** The SAMPE Model, RCRI and CCI comparison

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### Declarations of interest:

**Funding sources:** This study was supported by the Fundo de Incentivo à Pesquisa do Hospital de Clínicas de Porto Alegre (FIPE-HCPA- Project 16-0229). The funder had no role in study design, data collection and analysis, preparation of the manuscript, or decision to submit the article for publication.

**Author contributions:** *Claudia S. Gutierrez* helped with conceptualization, methodology, data collection, and wrote the manuscript. *Mariana L. Berto* and *Marina B. Lorenzen* helped with conceptualization, methodology and data collection. *Stela M. J. Castro* helped with methodology and statistical analyses. *Luana S. Giaretta* helped with methodology and data collection. *Wolnei Caumo* helped with conceptualization,

methodology and supervision of the study. *Luciana C. Stefani* helped with methodology, supervision and formal analysis of the study, conception and interpretation of the work, and wrote and revised the manuscript critically. All authors read and approved the final version of the manuscript.

## **Abstract**

**Study Objective:** The SAMPE risk model was designed to incorporate characteristics of an ideal risk model: it is easily applied at the bedside; it consists of few variables (age, ASA-PS, surgical severity, surgery type: emergency/elective) and has high discriminative power for 30-day postoperative in-hospital mortality. Our objectives were to compare the SAMPE risk model, the Revised Cardiac Risk Index (RCRI) and the Charlson Comorbidity Index (CCI) for predicting postoperative mortality, as well as to explore the association between SAMPE risk classes and postoperative morbidity.

**Design:** Retrospective cohort study over 24 months.

**Setting:** This study was conducted in an academic, quaternary medical center.

**Patients:** We reviewed medical records of 1206 patients aged above 16 years, submitted to non-cardiac surgeries.

**Intervention:** The probability of death according to the three risk indexes was calculated for each patient, using the variables researched in electronic medical records.

**Measurements:** The main outcome was 30-day postoperative in-hospital mortality. The accuracy of the SAMPE model, the RCRI, and the CCI were compared using C-statistic. Poisson regression with robust error variances was used to estimate the relative risk for each domain of the Postoperative Morbidity Survey according to the SAMPE risk class.

**Main Results:** The AUROC for the SAMPE model and the RCRI and CCI scores were 0.907 (0.84 - 0.93), 0.767 (0.69 - 0.83), and 0.822 (0.76 - 0.90), respectively. According to the DeLong test, there was a significant difference between the SAMPE and RCRI ( $p < 0.01$ ) and the SAMPE and CCI results ( $p < 0.028$ ). Postoperative morbidity occurred more frequently in patients with a higher probability of death.

**Conclusions:** The SAMPE model presented high discriminative power in this cohort, performing better than CCI or RCRI.

## **Keywords**

Risk assessment; Revised Cardiac Risk Index; Charlson Comorbity Risk; postoperative complication; postoperative mortality

## 1. Introduction

Accurate and timely identification of high-risk patients is strongly recommended by preoperative assessment guidelines [1–4]. The SAMPE (Anesthesia and Perioperative Medicine Service) model was designed to incorporate the characteristics of an ideal risk model: it is easily applied at bedside; it consists of small number of sustainable variables, including clinical data from the patient (age and American Society of Anesthesiologists (ASA) Physical Status Classification) and the procedure (surgical severity and surgery type: emergency or elective). The model had high discriminative power for 30-day postoperative in-hospital mortality [5]. However, for this new instrument to have wider perioperative use, it is essential to quantify its capacity to estimate the outcome and to evaluate its performance compared to common risk-prediction instruments.

Therefore, this study has two main aims. The first is to assess the SAMPE risk model's accuracy compared to the modified RCRI (mRCRI) score and the Charlson Comorbidity Index (CCI) for predicting postoperative mortality. The second is to explore the association between SAMPE risk classes and postoperative morbidity using the Postoperative Morbidity Survey (POMS). Our hypothesis was that the SAMPE model would more accurately predict postoperative mortality than the RCRI or the CCI. We also hypothesized that patients with a higher probability of death according to the SAMPE risk model would have a higher relative risk of postoperative complications.

## 2. Methods

### 2.1 Hospital setting, procedures and patients

This study was conducted in an academic, quaternary care center in southern Brazil. Ethical approval was granted by the Hospital de Clínicas de Porto Alegre Postgraduate Research Group Ethics Committee (Project number: 16-0229). Surgeries performed on patients over 16 years old, between January 2016 and December 31, 2017 whose complete data was stored in the information management system were included. We excluded cardiac surgeries, obstetric and diagnostic procedures and surgeries involving only local anesthesia. When more than one surgical procedure was performed during the same hospital admission, only the major procedure was taken into account for analysis. Written informed consent was not required, although a confidentiality agreement was necessary to access information from the institution database. The patients were followed for 30 days after surgery, even if they remained in the hospital for longer. The final study cohort consisted of 1206 patients.

### 2.2 Data collection

The variables needed to calculate the probability of postoperative in-hospital mortality for each model were compiled, as were the factors associated with postoperative morbidity. Data on patient characteristics and perioperative factors were collected by trained research staff. Preoperative risk variables, co-morbidities, and postoperative outcomes, such as mortality, hospital length of stay, reintervention, intensive care unit admission and postoperative morbidity, were obtained from patient notes or review of the electronic records from the information management system. The preoperative probability of death according to the three risk indexes was calculated for each patient, with the main outcome being in-hospital death or survival as recorded in the hospital discharge data. Patients were assessed for up to 30 days of hospitalization.

The SAMPE risk model was calculated according to a previously published equation [5].

A logistic regression model was adjusted to these four independent predictors: two patient-related (physical status and age), and two procedure-related (surgical severity and surgery type: emergency *vs* elective). The resulting probability of death was categorized in four classes: I, < 2%; II, between 2% and 5%; III, between 5% and 10%; IV, > 10%.

The CCI score was obtained by reviewing inpatient hospitalization records. Binary variables indicating the presence or absence of each comorbidity were created in the database. In Charlson's original method, scores were based on a weighted measure that incorporates age and 19 different medical categories; each is weighted according to its impact on mortality [6,7]. Age is adjusted by calculating each decade after 40 years of age as one point in the original age-adjusted CCI [7]. The modified RCRI was calculated by weighing the number of comorbidities: RCRI Class I - 0.4%, Class II - 0.9%, Class III – 6.6% and for Class IV - 11% [8].

Postoperative morbidity was recorded using the POMS (Table 1) on postoperative days 3 and 7. The POMS criteria were evaluated through a review of clinical notes, charts and data retrieval from the hospital clinical information system.

### *2.3 Statistical analysis*

Categorical data were expressed as absolute values (percentage) and continuous data as means (95% confidence intervals). To evaluate which risk method best predicted in-hospital postoperative mortality, their respective C-statistics were calculated. The C-statistic is equivalent to the area under the receiver operating characteristics (ROC) curve, or AUROC, i.e., the probability that someone who died had a higher predicted probability of mortality than someone who did not die in the specified time frame. A C-statistic of 0.5 indicates that the model's prediction is no better than chance, 0.7 to < 0.8 is acceptable, 0.8 to < 0.9 is excellent, 0.9 to < 1.0 is outstanding, and, 1.0 is perfect [9]. To

evaluate the accuracy of probabilistic prediction of the SAMPE model, we calculate the Brier Score. The Brier Score is defined as the average squared difference between the predicted probabilities and observed outcomes. To test the differences between two ROC curves, the DeLong test was used [10]. Calibration was evaluated by comparing observed and expected outcomes over different risk classes for each model or score [11]. We also conducted regression models, grouping the risk models or scores in classes. First, the SAMPE model and RCRI were categorized into four risk classes according to their original studies [5,8]. The CCI was categorized into four risk groups according to the recent age-adjusted index [12]. The frequency of postoperative morbidity according to the SAMPE model, RCRI and CCI risk classes were calculated. A Poisson regression model with robust error variances [13] was used to estimate the relative risk and confidence intervals for each POMS domain according to the SAMPE risk class model. SPSS version 22.0 (SPSS Inc., Chicago, IL) and R studio (version 3.6.0) were used for the statistical analyses. All tests were 2-sided, and alpha was set at 0.05.

### 3. Results

#### 3.1 Cohort description

The study flowchart can be seen in Fig. 1. During the 24 months of analysis, 1206 patients were included in the dataset used to compare the risk models. In this series, there were 43 postoperative deaths (3.56%). Table 1 describes the characteristics of the overall sample, stratified by the clinical and surgical variables of interest. Approximately 35% had an ASA physical status of 3 or greater, and 68% underwent intermediate or major surgical procedures.

The discriminatory power of each model in relation to in-hospital postoperative mortality was compared using the C-statistic, which is equivalent to the AUROC.

#### 3.2 Comparative accuracy of the SAMPE model, the RCRI and the CCI for predicting mortality

Fig. 2 illustrates the ROC curves for each model. The AUROCs for the SAMPE model, RCRI and CCI were 0.907 (0.84 - 0.93), 0.767 (0.69 - 0.83) and 0.822 (0.76 - 0.90), respectively. According to the DeLong test, there was a significant difference between SAMPE and RCRI results ( $p < 0.01$ ) and between the SAMPE and CCI results ( $p < 0.028$ ). There was no difference between RCRI and Charlson curves ( $p = 0.14$ ). The AUROC for ASA physical status score alone was also calculated, and its C-statistic was 0.85 (0.79 - 0.91), better than the CCI or RCRI. The Brier Score of the SAMPE model calculated was 0.0312.

A total of 43 patients died after surgery, which is a mortality rate of 3.56%. The SAMPE risk model predicted 38.4 deaths for the entire cohort, resulting in an overall ratio of observed to expected (O/E ratio) deaths of 1.11. The observed mortality was just 11% higher than that predicted by the model. All risk classes of the SAMPE model had an

accurate O/E ratio (near 1), except for class two (predicted mortality between 2% and 5%), in which the observed mortality was almost 60% higher than the predicted one.

We observed that all RCRI risk classes underestimated mortality for the entire cohort. This resulted in an overall prediction of 18 deaths and an O/E ratio of 2.39 (Table 2). Class II had the least ability to predict postoperative mortality (0.9%). The RCRI predicted 5 times fewer deaths than the number that occurred.

The CCI predicted 22 deaths, resulting in an overall O/E ratio of 1.95 (Table 2). In patients with a predicted risk of death  $\geq 7\%$ , the CCI predicted less than half of the deaths that occurred.

### *3.3 SAMPE prediction of morbidity risk*

The presence of complications was evaluated with the POMS scale on postoperative days 3 and 7. A total of 485 (40.4%) patients suffered at least one complication on day 3 and 208 (17.3%) did so on day 7. Fig. 3 shows the frequency of complications on the 3<sup>rd</sup> postoperative day according to SAMPE risk class.

Postoperative morbidity occurred more frequently in patients with a higher probability of death. A multivariate Poisson regression with a robust estimator was performed to calculate the relative risk of complications according to SAMPE model risk classes (Table 3). The relative risk of any complication on the third postoperative day increased significantly in higher SAMPE risk classes. Reliable confidence intervals related to the renal, infectious and gastrointestinal domains of the POMS scale confirmed the increased risk of complications at higher SAMPE risk classes.

## 4. Discussion

### 4.1 Principal findings

The main results of our study are the following:

- (a) Among patients over 16 years of age who underwent noncardiac surgery, the SAMPE risk model was more accurate at predicting postoperative in-hospital mortality than the RCRI or the CCI.
- (b) The SAMPE model's best clinical performance was obtained for very low-risk and high-risk patients, i.e. < 2% and > 5% probability of death, respectively. The CCI and RCRI indexes were poorly calibrated and underestimated mortality in all risk classes.
- (c) Higher risk classes of SAMPE model were predictors for postoperative complications on postoperative day 3 and 7, with the best results (lowest confidence interval) for renal, infectious and gastrointestinal complications.

### 4.2 Our results compared to the literature

The results show that the new SAMPE risk model had the best calibration and discrimination results for this cohort (C-statistic of 0.907, 95% CI: 0.84 - 0.93) and the best indices of observed *vs* expected deaths (close to 1 in most risk classes). Our model's advantages include that it encompasses well-defined risk factors for postoperative morbimortality, using an individualized combination of four variables weighted in a robust regression analysis for each patient [5]. All variables are ascertained in preoperative evaluation. The two patient-related variables are age and ASA physical status, while the two procedure-related variables are surgical severity (minor, intermediate or major) and surgery type (emergency *vs* elective). Our model involves variables that are similar to those in previously-published models [14–17], which strengthens the idea that both procedural and patient conditions must be incorporated to

optimize risk prediction. Moreover, our model includes only four variables, and the complete model equation is embedded in the calculator; thus, no approximation is required, and the end user does not need to deal with complex data. Data privacy and storage is not a concern, particularly because the application is designed to present only data. It is accompanied by a color-coded risk graphic indicating the probability of mortality.

The SAMPE model had better accuracy than both the RCRI and CCI. The RCRI was designed to predict only cardiac-related complications, and it does not include predictors of other important perioperative complications. It consists of six equally weighted variables: coronary artery disease, heart failure, cerebrovascular disease, diabetes mellitus requiring insulin therapy, renal insufficiency (creatinine concentration above 2 mg/dL) and high-risk noncardiac surgery (suprainguinal vascular, intrathoracic, or intraperitoneal procedures) [8]. Some studies investigating the performance of the RCRI have already demonstrated poor calibration and discrimination for predicting all-cause mortality, in spite of its wide use for predicting preoperative risk. A systematic review [18] that included over 790,000 patients and 6 studies reporting all-cause mortality showed that the RCRI's mortality prediction is poor (AUCs 0.62 -range, 0.54 to 0.78).

A recent study also found that the RCRI had an AUROC of 0.70 (0.67-0.72) for predicting in-hospital mortality, even with automated assessment [19]. Nevertheless, it performed well in the setting for which it was originally designed: predicting postoperative cardiac complications [20]. In our sample, the RCRI significantly underestimated mortality in all risk classes. We observed O/E ratios from 1.45 to 4.65. We should also consider that our sample consisted of general non-cardiac surgery, including emergency surgery. The cardiac complication incidence was lower than expected: 1.7% on the 3<sup>rd</sup> postoperative day and 0.9 on the 7<sup>th</sup>. This incidence agreed with

a recent publication comparing four cardiac risk calculators, in which the incidence of cardiac complications was 2.1% in 30 days [20]. Despite its simple calculation (one point for each variable), the RCRI is inadequate for general mortality prediction, which exceeds the cardiac focus of the original model.

The CCI is based on several conditions that are each assigned a weight from one to six, with a weight of six representing the most severe morbidity. The sum of the weighted comorbidity scores results in a summary score [6] that has been used in many clinical settings. Due to the CCI's widespread use, we compared its postoperative mortality prediction accuracy with that of the SAMPE model and the RCRI. Although we found that the CCI provided an accurate prediction of 30-day mortality (C-statistic, 0.83), the SAMPE model's performance was better (C-statistic was 0.90 p= 0.028) with only 4 variables.

#### *4.3 Strengths and limitations of the study*

This study's strengths include a large representative sample of adults undergoing noncardiac surgery. Outcome measurement was based on an individual chart review by a research team. Two classic stratification tools were used to validate the SAMPE model in a different sample. Performance for the main outcome, postoperative mortality, was determined with more than one measure (the C-statistic and observed vs predicted deaths). The TRIPOD Statement [21], a checklist for validating prediction models, was followed during the SAMPE model development.

The present study has some methodological limitations: (1) it was retrospective; (2) it was performed at a single academic medical center; (3) the true incidence of some complications could have been underestimated, since there was no routine active postoperative evaluation with troponin or electrocardiography, for example. Although the risk of complications on the 3<sup>rd</sup> and 7<sup>th</sup> postoperative days increased at higher SAMPE

risk classes, the few complications in some of the systems (e.g., cardiac, pulmonary and neurological) resulted in wide confidence intervals for complication prediction, which could have masked the relative risk value.

#### *4.4 Clinical implications*

The SAMPE model has been used as an online risk prediction instrument since 2017 [5]. It requires only preoperative data variables, its simplicity increases its chance of usage, and its performance is superior to frequently and widely validated risk stratification models. We also confirmed an association between postoperative morbidity and predicted mortality risk with the SAMPE model. This finding could make the SAMPE model an instrument for perioperative shared decision-making by predicting the 30-day postoperative mortality risk associated with a range of postoperative morbidity outcomes, such as infectious, renal and gastrointestinal complications. We also found that our model's best performance is in the risk class  $> 5\%$  of probability of death, which is the most important. In this class the SAMPE risk model showed an excellent O/E ratio, very close to 1 (from 0.97 to 1.11), unlike the RCRI and CCI, which underestimated the probability of death in all risk classes.

#### *4.5 Future implications*

External validation of SAMPE at other institutions is necessary to ensure a representative model for broad use. Regarding perioperative enhancement, the most important issue is to identify high-risk class patients, which our model does, with a robust statistical strategy. Considering the growth of health care costs and the need to compare performance among institutions, the SAMPE risk model can be used for local audits to assess predicted vs observed mortality. Furthermore, a risk model should help guide changes and determine appropriate care stratification. In an effort to target high-risk patients, the Excare

Research Group is currently working on the next step, comparing the outcomes of 48-hour postoperative co-managed care to normal postoperative ward care in a study called “A framework for screening and implementing extended specialized perioperative care for high-risk surgical patients” (CAE 04448018.8.0000.5327).

#### *4.6. Conclusion*

According to the analytic methods used to determine the prognostic accuracy of the SAMPE model, it can be considered a consistent instrument with easily verifiable preoperative variables that is capable of predicting 30-day postoperative mortality. Nevertheless, it cannot classify which patients will have better outcomes. The purpose of validating a preoperative risk model is to develop an instrument that helps provide more personalized care. We must consider how technology and real-world data, which compound risk models, can improve perioperative decision making, the risk information that can be provided to patients and their families, and the selection of special postoperative assistance to reduce complications and failure to rescue.

### **Acknowledgements**

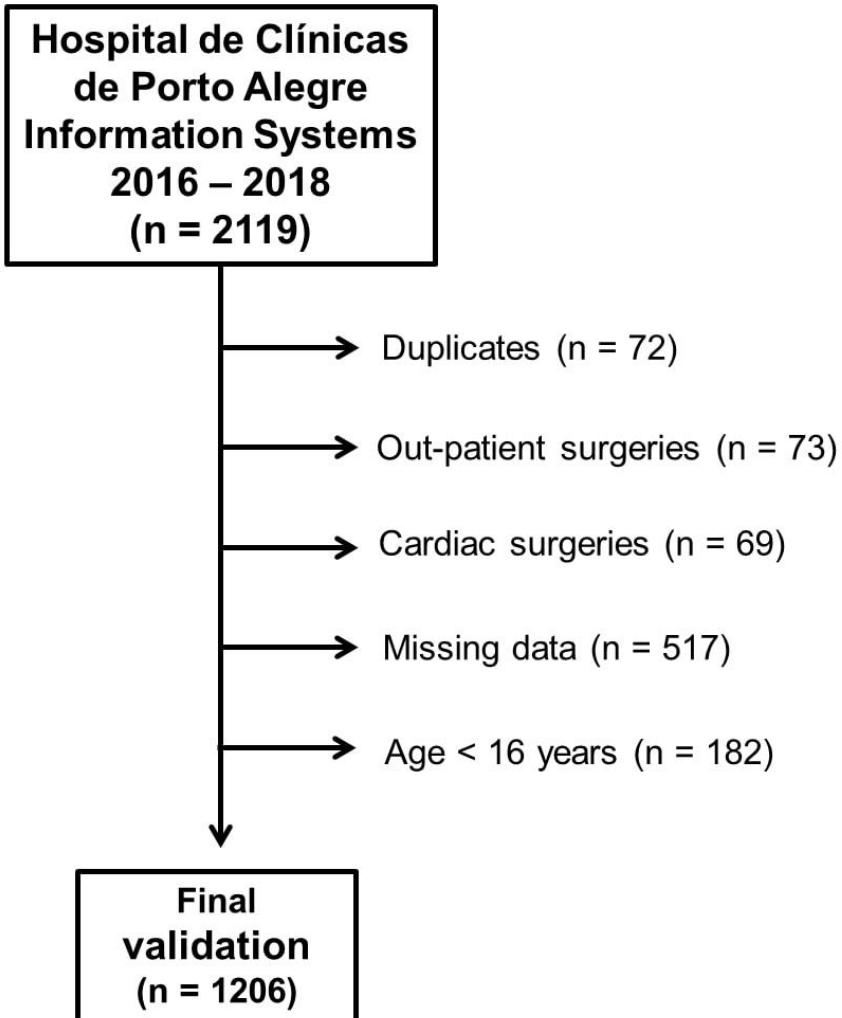
The authors would like to thank the following governmental Brazilian agencies: Fundo de Incentivo à Pesquisa do Hospital de Clínicas de Porto Alegre (FIPE-HCPA); and Postgraduate Research Group at the Hospital de Clínicas de Porto Alegre.

## References

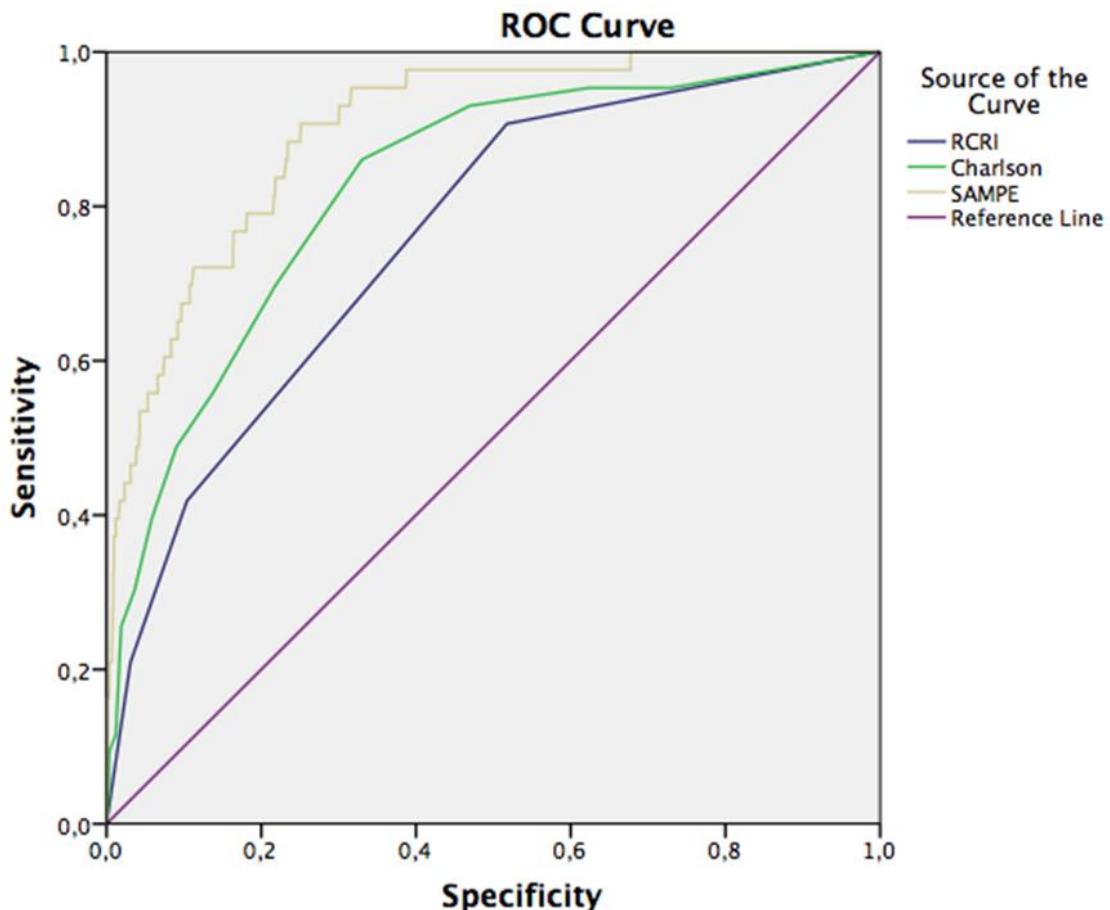
- [1] Duceppe E, Parlow J, MacDonald P, Lyons K, McMullen M, Srinathan S, et al. Canadian Cardiovascular Society Guidelines on Perioperative Cardiac Risk Assessment and Management for Patients Who Undergo Noncardiac Surgery. *Can J Cardiol* 2017;33:17–32. doi:10.1016/j.cjca.2016.09.008.
- [2] Moonesinghe SR, Mythen MG, Das P, Rowan KM, Grocott MPW. Risk Stratification Tools for Predicting Morbidity and Mortality in Adult Patients Undergoing Major SurgeryQualitative Systematic Review. *Anesth Analg* 2013;119:959–81. doi:10.1097/ALN.0b013e3182a4e94d.
- [3] Gualandro D, Yu P, Caramelli B, Marques A, Calderaro D, Fornari L, et al. 3rd Guideline for Perioperative Cardiovascular Evaluation of the Brazilian Society of Cardiology. *Arquivos Brasileiros de Cardiologia* 2017;109. doi:10.5935/abc.20170140.
- [4] Fleisher LA, Fleischmann KE, Auerbach AD, Barnason SA, Beckman JA, Bozkurt B, et al. 2014 ACC/AHA guideline on perioperative cardiovascular evaluation and management of patients undergoing noncardiac surgery: executive summary: a report of the American College of Cardiology/American Heart Association Task Force on practice guidelines. Developed in collaboration with the American College of Surgeons, American Society of Anesthesiologists, American Society of Echocardiography, American Society of Nuclear Cardiology, Heart Rhythm Society, Society for Cardiovascular Angiography and Interventions, Society of Cardiovascular Anesthesiologists, and Society of Vascular Medicine Endorsed by the Society of Hospital Medicine. *J Nucl Cardiol* 2015;22:162–215. doi:10.1007/s12350-014-0025-z.
- [5] Stefani LC, Gutierrez CDS, Castro SMDJ, Zimmer RL, Diehl FP, Meyer LE, et al. Derivation and validation of a preoperative risk model for postoperative mortality (SAMPE

- model): An approach to care stratification. PLoS ONE 2017;12. doi:10.1371/journal.pone.0187122.
- [6] Charlson, Mary; Pompei, Peter; Ales, Kathy and MacKenzie Ronald. A New Method of Classifying Prognostic Comorbidity in Longitudinal Studies: Development and Validation. *J Chron Dis* 1987;40:373–83.
- [7] Charlson M, Szatrowski TP, Peterson J, Gold J. Validation of a combined comorbidity index. *J Clin Epidemiol* 1994;47:1245–51.
- [8] Lee TH, Marcantonio ER, Mangione CM, Thomas EJ, Polanczyk CA, Cook EF, et al. Derivation and Prospective Validation of a Simple Index for Prediction of Cardiac Risk of Major Noncardiac Surgery. *Circulation* 1999;100:1043 LP – 1049. doi:10.1161/01.CIR.100.10.1043.
- [9] Cook NR. Statistical evaluation of prognostic versus diagnostic models: beyond the ROC curve. *Clin Chem* 2008;54:17–23. doi:10.1373/clinchem.2007.096529.
- [10] DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics* 1988;44:837–45.
- [11] Spiegelhalter DJ. Funnel plots for comparing institutional performance. *Stat Med* 2005;24:1185–202. doi:10.1002/sim.1970.
- [12] Chang C-M, Yin W-Y, Wei C-K, Wu C-C, Su Y-C, Yu C-H, et al. Adjusted Age-Adjusted Charlson Comorbidity Index Score as a Risk Measure of Perioperative Mortality before Cancer Surgery. *PLoS ONE* 2016;11:e0148076. doi:10.1371/journal.pone.0148076.
- [13] Zou G. A modified poisson regression approach to prospective studies with binary data. *Am J Epidemiol* 2004;159:702–6. doi:10.1093/aje/kwh090.

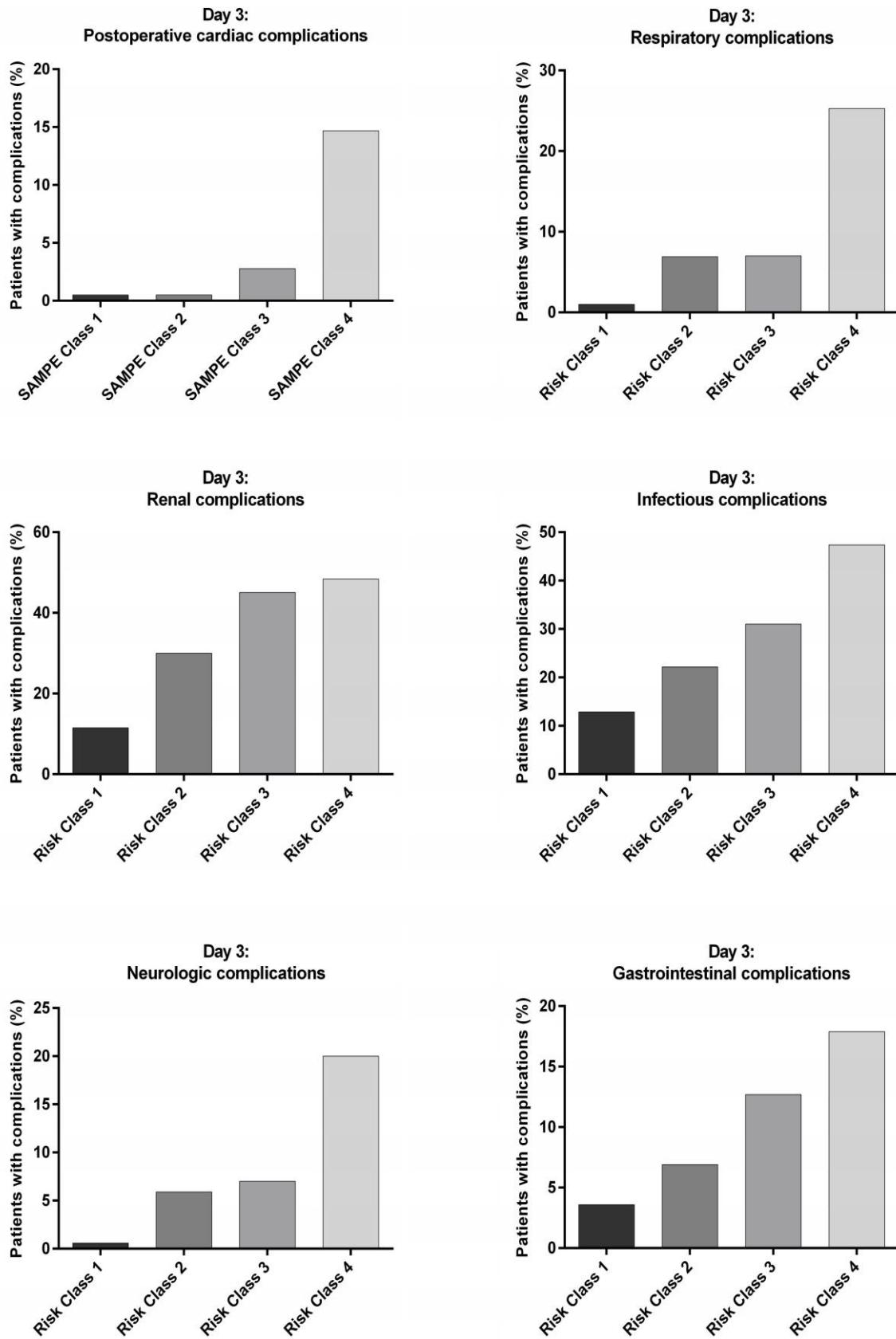
- [14] Sutton R, Bann S, Brooks M, Sarin S. The Surgical Risk Scale as an improved tool for risk-adjusted analysis in comparative surgical audit. *Br J Surg* 2002;89:763–8. doi:10.1046/j.1365-2168.2002.02080.x.
- [15] Glance LG, Lustik SJ, Hannan EL, Osler TM, Mukamel DB, Qian F, et al. The Surgical Mortality Probability Model: derivation and validation of a simple risk prediction rule for noncardiac surgery. *Ann Surg* 2012;255:696–702. doi:10.1097/SLA.0b013e31824b45af.
- [16] Donati A, Ruzzi M, Adrario E, Pelaia P, Coluzzi F, Gabbanelli V, et al. A new and feasible model for predicting operative risk. *Br J Anaesth* 2004;93:393–9. doi:10.1093/bja/aeh210.
- [17] Protopapa KL, Simpson JC, Smith NCE, Moonesinghe SR. Development and validation of the Surgical Outcome Risk Tool (SORT). *Br J Surg* 2014;101:1774–83. doi:10.1002/bjs.9638.
- [18] Ford MK, Beattie WS, Wijeyesundara DN. Systematic review: prediction of perioperative cardiac complications and mortality by the revised cardiac risk index. *Ann Intern Med* 2010;152:26–35. doi:10.7326/0003-4819-152-1-201001050-00007.
- [19] Hofer IS, Cheng D, Grogan T, Fujimoto Y, Yamada T, Beck L, et al. Automated Assessment of Existing Patient's Revised Cardiac Risk Index Using Algorithmic Software. *Anesth Analg* 2019;128:909–16. doi:10.1213/ANE.0000000000003440.
- [20] Cohn SL, Fernandez Ros N. Comparison of 4 Cardiac Risk Calculators in Predicting Postoperative Cardiac Complications After Noncardiac Operations. *American Journal of Cardiology* 2018. doi:10.1016/j.amjcard.2017.09.031.
- [21] Collins GS, Reitsma JB, Altman DG, Moons KGM, members of the TRIPOD group. Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD): The TRIPOD Statement. *Eur Urol* 2015;67:1142–51. doi:10.1016/j.eururo.2014.11.025.



**Fig. 1.** Study flowchart.



**Fig. 2.** ROC curves of the SAMPE model, the RCRI, and the CCI for predicting postoperative in-hospital mortality. The AUROCs for the SAMPE model, the RCRI, and the CCI were 0.907 (95% CI: 0.84 - 0.93), 0.767 (95% CI: 0.69 - 0.83) and 0.822 (95% CI: 0.76 - 0.90), respectively. AUROC, area under the curve of receiver operating characteristics; CCI, Charlson Comorbidity Index; CI, confidence interval; RCRI, Revised Cardiac Risk Index; ROC, receiver operating characteristics; SAMPE, Service of Anesthesia and Perioperative Medicine.



**Fig. 3.** POMS individual morbidity domains on the 3<sup>rd</sup> postoperative day. POMS, Postoperative Morbidity Survey.

**Table 1** Characteristics of the overall sample and 30-day in-hospital postoperative deaths, stratified by clinical and surgical predictors.

	<b>Total sample n= 1206 (100%)</b>	<b>Postoperative deaths n= 43 (3.56%)</b>
<b>Age (years)</b>		
16 - 35	197 (16.33%)	1 (0.50%)
36 - 55	388 (32.17%)	7 (1.80%)
56 - 75	490 (40.63%)	20 (4.08%)
> 76	131 (10.86 %)	15 (11.45%)
<b>Gender</b>		
Male	508 (42.14%)	19 (3.74%)
Female	698 (57.87%)	24 (3.43%)
<b>ASA Physical Status</b>		
1	137 (11.35%)	1 (0.72%)
2	640 (53.06%)	2 (0.31%)
3	394 (32.66%)	23 (5.83%)
4	34 (2.81%)	17 (50.00%)
5	1 (0.08%)	0 (0%)
<b>Surgery type</b>		
Elective	1020 (84.58%)	21 (2.05%)
Emergency	186 (15.42%)	22 (11.82%)
<b>Surgical severity</b>		
Minor	377 (31.26%)	8 (2.12%)
Intermediate	506 (41.96%)	9 (1.77%)
Major	323 (26.78%)	26 (8.04%)

ASA: American Society of Anaesthesiologists.

**Table 2** Mortality Predictions of the SAMPE model, the RCRI and the CCI.

<b>Risk model categories</b>	<b>Mean risk (%)</b>	<b>Number (%) of patients n= 1206</b>	<b>Expected deaths</b>	<b>Observed deaths n= 43</b>	<b>Observed vs expected death ratio</b>
<b>SAMPE risk model</b>			29		1.53
Class I	< 2%	842 (69.81%)	4.21	5 (0.59%)	1.18
Class II	>2 < 5%	212 (17.57%)	6.44	11 (5.18%)	1.70
Class III	>5 <10%	94 (7.79%)	6.62	6 (6.38%)	0.90
Class IV	>10%	58 (4.80%)	11.61	21 (36.20%)	1.80
<b>RCRI</b>			18		2.39
Class I	0.4%	565 (46.84%)	2.26	4 (0.70%)	1.77
Class II	0.9%	502 (41.62%)	4.52	21 (4.18%)	4.65
Class III	6.6%	94 (7.79%)	6.20	9 (9.57%)	1.45
Class IV	11%	45 (3.73%)	4.95	9 (20.00%)	1.82
<b>CCI score</b>			22		1.95
0 - 3	0.9%	785 (65.4%)	7.06	6 (0.8%)	0.85
4 - 7	2.9%	331 (27.6%)	9.6	15 (4.5%)	1.56
7 - 12	7.0%	77 (6.4%)	5.39	13 (16.9%)	2.41
> 12	13.2%	8 (0.7%)	1.06	4 (50%)	3.77

Abbreviations: CCI, Charlson Comorbidity Index; SAMPE, Anesthesia and Perioperative Medicine Service;

RCRI, Revised Cardiac Risk Index. The mean risk prediction of each SAMPE class was considered: Class I=

0.5%; Class II= 3.04%; Class III= 7.05%; Class IV= 20.02%.

**Table 3** Multivariable Poisson Regression of SAMPE risk classes and postoperative complications according to the POMS.

	Relative risk of SAMPE risk classes (confidence interval)						
	<i>Class I</i> <i>&lt; 2%</i>	<i>Class II</i> <i>2% - 5%</i>	<i>p</i>	<i>Class III</i> <i>5% - 10%</i>	<i>p</i>	<i>Class IV</i> <i>&gt; 10%</i>	<i>p</i>
Complication on 3 <sup>rd</sup> 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 7 <sup>th</sup> 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
<b>Morbidity according POMS domains on 3<sup>rd</sup> postoperative day</b>							
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
Hematological	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

POMS, Postoperative Morbidity Survey; SAMPE, Anesthesia and Perioperative Medicine Service.

STROBE Statement—Checklist of items that should be included in reports of *cohort studies*

	<b>Item No</b>	<b>Recommendation</b>	<b>Page</b>
<b>Title and abstract</b>	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	84
		(b) Provide in the abstract an informative and balanced summary of what was done and what was found	84
<b>Introduction</b>			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	85
Objectives	3	State specific objectives, including any prespecified hypotheses	85
<b>Methods</b>			
Study design	4	Present key elements of study design early in the paper	86
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	86
Participants	6	(a) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	86-87
		(b) For matched studies, give matching criteria and number of exposed and unexposed	NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	86-87
Data sources/measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	86-87
Bias	9	Describe any efforts to address potential sources of bias	NA
Study size	10	Explain how the study size was arrived at	NA
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	86-87
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	86-87
		(b) Describe any methods used to examine subgroups and interactions	86-87
		(c) Explain how missing data were addressed	NA
		(d) If applicable, explain how loss to follow-up was addressed	NA
		(e) Describe any sensitivity analyses	NA
<b>Results</b>			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	89-90
		(b) Give reasons for non-participation at each stage	100
		(c) Consider use of a flow diagram	100
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	103
		(b) Indicate number of participants with missing data for each variable of interest	NA
		(c) Summarise follow-up time (eg, average and total amount)	90
Outcome data	15*	Report numbers of outcome events or summary measures over time	89-90

Main results	16	(a) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included  (b) Report category boundaries when continuous variables were categorized  (c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA 87; 104 105-106
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	NA
<b>Discussion</b>			
Key results	18	Summarise key results with reference to study objectives	91
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	93-94
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	91-94
Generalisability	21	Discuss the generalisability (external validity) of the study results	93-94
<b>Other information</b>			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	82

\*Give information separately for exposed and unexposed groups.

**Note:** An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at <http://www.plosmedicine.org/>, Annals of Internal Medicine at <http://www.annals.org/>, and Epidemiology at <http://www.epidem.com/>). Information on the STROBE Initiative is available at <http://www.strobe-statement.org>.

7.3 ARTIGO 3 - EFFECTIVENESS OF A PACU POSTOPERATIVE PATHWAY  
TRIGGERED BY A NEW PREOPERATIVE STRATIFICATION TOOL (SAMPE  
MODEL): IMPACT OF POSTOPERATIVE DETERIORATION

**Title Page**

**Title:** Effectiveness of a PACU postoperative pathway triggered by a new preoperative stratification tool (SAMPE model): impact on postoperative deterioration

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**Declarations of interest:** None.

**Funding:** This study was supported by Project 2016-0229 from the Fundo de Incentivo à Pesquisa do Hospital de Clínicas de Porto Alegre (FIPE-HCPA). The funder had no role in study design, data collection and analysis, preparation of the manuscript, or decision to submit the article for publication.

## Abstract

**Background:** Practical use of risk predictive tools, as well as assessment of their impact on outcome reduction, is still a challenge. We describe the implementation of a postoperative death risk stratification model (SAMPE Model) in the post-anaesthetic recovery room and to evaluate its impact on the incidence of postoperative Rapid Response Teams (RRT) calls.

**Methods:** Design: Prospective cohort with historical controls over a 12-month period. Setting: Surgical Centre of a Quaternary-level University Hospital. Patients: 5,353 patients over 16 years undergoing non-cardiac surgery. Measurements: The four variables that compose the SAMPE model (age, ASA-PS, surgical severity, and type) were measured, and patients were categorized according to their risk. Specific discharge criteria were adopted for high-risk patients. RRT calls within 48 hours and 30 postoperative days were measured before and after implementation of the SAMPE model.

**Results:** Mortality was 1.68% (n= 90), and incidence of RRT calls was 4.37% (n= 234) at 30 days. With all four risk classes combined, there was no difference in the total number of RRT calls before and after the implementation of the SAMPE model ( $p=0.60$ ). However, we found a reduction in the proportion of RRT calls in high-risk ( $p=0.05$ ) compared to low-risk patients.

**Conclusions:** Employing a risk tool to guide immediate postoperative care may influence postoperative deterioration. Labelling patients may optimise the handover and ground differentiated care for high-risk patients.

**Keywords:** risk assessment; risk stratification; postoperative period; rapid response team; clinical deterioration.

*Abbreviations:* ASA-PS, American Society of Anaesthesiologists Physical Status; HCPA, Hospital de Clínicas de Porto Alegre; ICU, Intensive Care Unit; PACU, Post Anaesthetic Care Unit; RRT, Rapid Response Team.

## 1. Introduction

High-risk surgical patients account for about 80% of postoperative deaths, a high proportion of complications, and prolonged periods of hospitalisation [1,2]. They are especially vulnerable to the several moments of perioperative transitions of care, often between professionals from different areas, with distinct knowledge, training, perspectives, and expectations [3]. In addition to the classical, mostly non-modifiable risk factors related to comorbidities and surgical trauma, the treatment of high-risk surgical patients in hospitals determines their outcomes [4]. Pathways to improve perioperative assistance based on quality improvement programs have been proposed, but their efficacy still needs to be evaluated in different contexts [5]. Therefore, it seems reasonable to include consistent, statistically oriented tools in perioperative decisions to identify high-risk surgical patients by improving judgment accuracy and to support behaviours and processes that increase patients' safety [6].

Ideally, a prognostic model should be simple, accurate, include few variables, and be developed and validated in the target population [7]. In this context, we developed an accurate model to predict in-hospital death within 30 days after surgery: the SAMPE Model. It consists of four variables collected preoperatively: ASA-PS classification, patient age, severity of surgery, and nature of surgery (elective versus urgent). Patients were categorized into four risk classes according to the predicted probability of death: Class I ( $p < 2\%$ ); Class II ( $2\% \leq p > 5\%$ ); Class III ( $5\% \leq p > 10\%$ ); and Class IV ( $\geq 10\%$ ) [8].

Identifying high-risk patients is just the first step in planning risk-adapted perioperative care. Anaesthesiologists are well-positioned to lead the re-engineering of perioperative care pathways. Thus, we initiated a quality improvement program at the Post-

Anaesthetic Care Unit (PACU) based on improving the identification of high-risk patients, adopting a distinct discharge checklist and optimising handover.

The present study aimed to describe the preoperative adoption of a new Postoperative Death Probability Model (SAMPE model) and evaluate the impact of the incorporation of a PACU pathway for high-risk surgical patients on postoperative deterioration measured by the incidence of Rapid Response Team (RRT) calls in the postoperative period. We hypothesised that, by stratifying patients with an instrument for objective risk measurement and individualising postoperative care by an immediate postoperative high-risk surgical path, we might improve postoperative care and reduce clinical deterioration of high-risk patients.

## 2. Methods

We conducted a prospective cohort study, a before and after study (quasi-experiment) comparing two groups: one before and one after incorporation of the SAMPE Model into clinical practice in the immediate postoperative period.

### *2.1 Institutional setting*

The study took place at Hospital de Clínicas de Porto Alegre (HCPA), a university hospital in southern Brazil. The hospital is a quaternary-level health centre that performs approximately 12,000 procedures per year of varying levels of complexity. The PACU consists of 18 adult beds and 5 paediatric beds and receives patients undergoing various types of surgery.

Ethical approval was provided by the Ethical Committee for Postgraduate and Research Group from the HCPA – Brazil (project number 2016-0029).

### *2.2 Data source and study population*

Data were collected from surgical patients over 16 years of age, referred directly to the recovery room immediately after their procedure, from August 2016 to January 2017. We excluded from the analysis patients referred directly to the intensive care unit (ICU); who underwent cardiac surgery, obstetric procedures, or outpatient procedures; or under local anaesthesia. Patients admitted to the recovery room between 7:00 pm and 7:00 am and on weekends were also excluded. For patients who underwent more than one surgery, only the major procedure was included in the analysis. Data were collected by a team of trained researchers from the Anaesthesia and Perioperative Medicine Service, using information from the medical records and the Hospital's integrated information system. The controls were patients who underwent surgery at the same institution submitted to the usual care, 6 months prior to the beginning of the intervention.

### *2.3 Immediate postoperative care pathway based on SAMPE Model categorisation*

To calculate the predicted probability of death, a digital table shared on Google Docs was created, allowing the insertion of all possible combinations of the 4 variables that make up the model: patient age, ASA-PS classification, surgical severity and elective or urgent/emergency nature. This digital tool was shared with the hospital anaesthetist team. Patients were categorised into four risk classes according to the predicted probability of death: Class I ( $p < 2\%$ ); Class II ( $2\% \leq p > 5\%$ ); Class III ( $5\% \leq p > 10\%$ ); and Class IV ( $\geq 10\%$ ) [8]. After derivation and validation of the risk model (SAMPE Model), we developed a quality-improvement program to improve the care of high-risk patients at the PACU.

Educational meetings and training with the anaesthesiology team and the nursing staff were held to implement the immediate postoperative care pathway at the recovery room using the Model for Improvement Methodology [9].

During those educational meetings, the research team discussed the need to categorise the patients at the PACU. They also shared concerns about suboptimal care of high-risk patients at the recovery room when the usual discharge checklist is applied for all patients without distinction.

Staff training occurred throughout 12 weeks, including visual presentations and interactive meetings to identify barriers and solutions to facilitate the implementation of the new pathway.

The key features of the immediate postoperative care pathway for the high-risk patients were:

- (1) Calculation of the predicted probability of death and its respective risk class according to the SAMPE model by the anaesthesiologist of the surgical room, and registration of this information in the anaesthesia manual record;

- (2) Visual identification of the patient through colour cards placed above the bed headboard in the PACU, with one colour for each of the four SAMPE Model risk classes;
- (3) Implementation of a distinct discharge-to-ward checklist for patients classified as high-risk and very high-risk (classes III and IV).

The recommended discharge checklist for high-risk patients included assessment of fluid balance and urine output; verification of laboratory tests and the need for new ones; review of medical prescriptions; and a written discharge plan, in addition to the standard checklist employed in the institution, based on the Aldrete-Kroulik and White scales (Table S1 - Supplementary Material).

Discharge of high-risk patients by the PACU nurse included a report on the electronic medical record and a handover phone call to the common ward nurse.

Additionally, for low-risk patients (probability of death < 2%) with uncomplicated postoperative course, the nurse handover process was simplified, without the need for handover phone calls from the PACU nurse to the ward nurse (Fig.1).

#### *2.4 Outcomes*

The primary outcome measure was postoperative clinical deterioration assessed by RRT calls within 48 hours and within 30 postoperative days. The secondary outcome was in-hospital death within 30 days.

RRT activation was conditioned on the occurrence of the following triggers indicative of clinical deterioration: airway at risk (need for ventilatory support); respiratory rate < 8 or > 35 breaths/min; oxygen saturation < 90%; heart rate < 40 or > 140 beats/min; systolic blood pressure < 90 mmHg; decrease in the Glasgow coma scale  $\geq 2$  points; prolonged (> 5 minutes) or repeated seizure.

#### *2.5 Statistical analysis*

We evaluated the impact of incorporating the PACU postoperative pathway with a “before and after” analysis. The outcomes were occurrence of RRT calls within 48 hours and within 30 postoperative days. By using hospital data provided by the RRT team, we estimated that between 8 and 10% of surgical patients would require RRT calls within 30 days, regardless of risk class.

With a 5% significance level and a statistical power of 90%, a sample size of 1,615 patients in each group would be necessary to detect an RRT reduction of 25% in the intervention group versus the usual care group. A robust variance logistic regression model (Poisson model) was used to compare the proportion of RRT calls between groups and risk classes according to the SAMPE Model. We analysed the data using the SAS Studio software version 9.4.

### 3. Results

Data from a final retrospective cohort of 2,820 and a prospective cohort of 2,533 patients were analysed, including 234 RRT calls within 30 days (4.37%).

From August 1, 2016 to January 31, 2017, 2,533 patients were stratified according to the SAMPE Model during pre-anesthetic evaluation. They were submitted to the immediate postoperative high-risk pathway if the probability of death exceeded 5%. The control group was a retrospective cohort of 2,820 patients, submitted to usual care without risk stratification from January to July 2016. Fig. 2 shows the potential inclusion in each group and the individuals included in the final analysis of the primary endpoint. Table 1 shows the population characteristics of the intervention and control groups.

#### *3.1 Prediction and prevention of postoperative deterioration*

The majority of RRT calls occurred within the first three postoperative days (71.48%, n = 168). The main triggers for RRT calls were oxygen saturation < 90% (38.88%, n = 91) and systolic blood pressure < 90 mmHg (34.61%, n = 81). In 29.63% (n = 67) of the patients, sepsis was suspected.

SAMPE risk class was an independent predictor of RRT calls within 48 hours, regardless of group ( $p < 0.001$ ). A difference was observed when comparing risk class I with the other risk classes ( $p < 0.05$ ) (data summarised in Fig. 3).

We did not find a significant difference in the total proportion of RRT calls between the control and intervention groups at 48 hours or at 30 days. However, when SAMPE risk classes were analysed separately, we observed an effect of intervention, consisting of a reduction in RRT calls in class IV (probability of death > 10%) at 30 days. There was an interaction between group and risk class ( $p < 0.01$ ) and a difference between risk classes regardless of group ( $p < 0.001$ ). We observed an increase in the proportion of

RRT calls in class II patients and a reduction in classes III and IV after implementation of the SAMPE Model in the PACU. The results are summarised in Table 2.

### *3.2 Postoperative mortality*

In-hospital mortality in the total sample was 1.68% ( $n = 90$ ). We did not find a difference between the control and intervention groups regarding in-hospital postoperative mortality within 30 days. The mortality rate of patients treated by the RRT was 10 times higher, 19.57% ( $n = 46$ ). Of the patients who died, 53% ( $n = 48$ ) underwent major surgery; 54% ( $n = 49$ ) of the surgeries were urgent; and 78% ( $n = 71$ ) of the patients were classified as ASA 3 or 4. Table 3 shows the mortality by SAMPE risk class, with high-risk patients (12% of the total) accounting for 66% of all deaths. The main cause of death was sepsis, followed by advanced cancer. The frequencies of death causes (90 cases) are available in Fig. S1 (Supplementary Material).

#### 4. Discussion

The main finding of this study was the reduction of postoperative 30-day RRT calls in the very high-risk patient group who underwent a PACU postoperative pathway for high-risk patients. Unexpectedly, we found an increase in the number of RRT calls for intermediate-risk class patients. No survival benefit was achieved by this intervention. Furthermore, we confirmed that the small group of high-risk patients (13% of the total) had a higher proportion of RRT calls (40%) and accounted for 2/3 of postoperative deaths.

We described the implementation of an achievable postoperative pathway based on information about patients' risk and consisting of changes restricted to the immediate postoperative period. By incorporating a risk stratification tool to inform the patients' risk, we sought to objectively identify highest-risk patients in the PACU and to provide differentiated care and discharge plans for those patients. However, after discharge from the PACU, all patients received standard care according to the inpatient unit routines. This fragmentation of care and the transition of high-risk patients between environments – from a monitored environment with a higher nurse:bed ratio to the low acuity general hospital ward without a continuous care pathway – might have contributed to the absence of more expressive results. Furthermore, this brief intervention, carried out during a limited period and focused on improving the care of high-risk patients at the PACU, might have led to an unsought suboptimal care of low-risk patients. Additionally, our sample included a small number of patients in the high-risk categories (13%) compared to the lower risk ones, and a small number of RRT calls in the postoperative period. The frequency of RRT calls was below our estimates when computing our sample size. The exclusion of weekend and night surgeries certainly contributed to the high proportion of low-risk patients in our sample.

High-risk procedures, non-elective surgeries and ASA classification 3 or higher were the main risk factors for death in the cohort investigated, and this association has already been described in the literature [10–13]. Although mortality is one of the outcomes commonly considered in analyses of impact of new health strategies, some caveats must be mentioned concerning the treatment of surgical patients. Mortality directly related to anaesthesia and surgery has declined in recent decades, and the study of the relationship between morbidity and postoperative complications and surgical mortality has increased. By analysing only the mortality rate, we were unable to distinguish between potentially preventable deaths and inevitable deaths [14,15]. The death rate secondary to a postoperative complication – failure to rescue – has been used as a robust metric to assess health service quality. This measure may reflect the system's ability to identify their risk population, conduct early diagnosis and treatment of patients with clinical deterioration, and scale-up care appropriately [6,16,17]. The activation triggers of RRT are potential markers of clinical deterioration and may indicate a need of medical intervention. Mortality in the group of patients treated by the RRT in our study was close to 20%, confirming this index as a reliable indicator of clinical worsening [18–20].

In this context, few studies address the implementation strategy and the impacts of using individual stratification to guide surgical decision making, or of employing a coordinated approach, focused on the patient and involving teamwork among all disciplines involved in care before, during, and after surgery [21–23]. Recent results of the EPOCH study, a large-scale national quality improvement (QI) program to implement a care pathway for patients undergoing emergency abdominal surgery, showed no survival benefits. The results were attributed to variation between hospitals in fidelity of implementation, prioritisation of pathway components, and the time

required to achieve effective change. The study suggests that QI programs should implement fewer, more discrete changes and ensure that leadership teams have adequate time to achieve sustained improvements in patient care [24].

Even though medical decision-making processes are grounded in logic and probability, evidence indicates that other factors that are difficult to measure, such as individual preferences, cognitive biases, emotions, and previous experiences, play a role in multiple levels of the decision tree [25]. Hence, it seems reasonable to include consistent, statistically oriented tools in the decision process to improve judgment accuracy and support behaviours that increase patient safety [26].

#### *4.1 Study strengths and limitations*

The main strengths of this study include a large sample size: a cohort of 5,353 patients undergoing various types of surgery; and the demonstration that discrete changes in PACU processes ensured by the postoperative leadership teams could be effective in improving outcomes and boosting expanded postoperative pathways. Anticipating difficulties in implementing a comprehensive improvement program, we initially focused on sensitising caregivers to the importance of recognising high-risk patients and of implementing immediate postoperative actions in preparation for future extended postoperative interventions.

The main limitations of our study include limited external validity and problems inherent to its design, a quasi-experimental study with historical controls. Changes in clinical practice and due to temporal factors may have influenced the results. Additionally, data from patients who suffered postoperative complications and were treated by their assisting physician without triggering the RRT were not analysed. It is known that the triggering of RRT is influenced by several variables of the system in

which the team operates, such as identification of clinical deterioration, experience of the nursing staff, institutional safety culture and availability of medical teams [27,28].

To facilitate the training and adherence of the health providers, we included only patients from the day shifts. Some studies indicate that patients who underwent surgery at night and on weekends have a higher risk of death, although the literature on this issue is conflicting [29,30].

Finally, fragmented assistance, inadequate preoperative assessment, and suboptimal care at the ward minimise the PACU care capacity to provide substantial benefit to the patients. In this context, our proposed PACU pathway for high-risk patients is limited. Consistent perioperative teamwork and care coordination should be planned according to each setting, aiming at long-term postoperative outcomes [31].

#### *4.2 Study contributions and future perspectives - ExCARE Project (Extended Care in High-Risk Surgical Patients)*

Considering that the high-risk surgical population is responsible for the largest number of postoperative complications and deaths and that postoperative care should ideally be individualised, such care must extend beyond the boundaries of the operating room. For the patient, the surgical journey begins when the surgery is decided upon in primary care and ends weeks to months after the procedure [32].

Measures proposed to address the challenge of improving patient experience and population health while reducing costs include risk-adapted postoperative management focused on the improvement of handover processes; better decisions concerning postoperative allocation; and well-designed ward processes aiming at avoiding failure-to-rescue [33].

Accordingly, our goal is the evaluation of an extended pathway based on two actions (ExCare pathway). The first is improving nurse-physician communication. The second

consists of closely monitoring vital signs of high-risk surgical patients – identified by the SAMPE risk stratification tool – for 48 hours during the postoperative period in the ward. We believe that the adoption of perioperative care pathways compatible with individual risks may improve patient experience and produce better outcomes in the surgical journey (Fig. 4).

## 5. Conclusions

This study described the implementation and impact of a PACU postoperative pathway based on actions directed at high-risk surgical patients identified by the SAMPE Model. Patients classified as high-risk had a higher proportion of RRT calls at 48 hours and at 30 postoperative days. We observed a reduction in the proportion of RRT calls in the high-risk group. Further work is needed on more robust strategies involving health providers in a comprehensive manner to develop quality improvement interventions for high-risk patients adapted to each reality.

## References

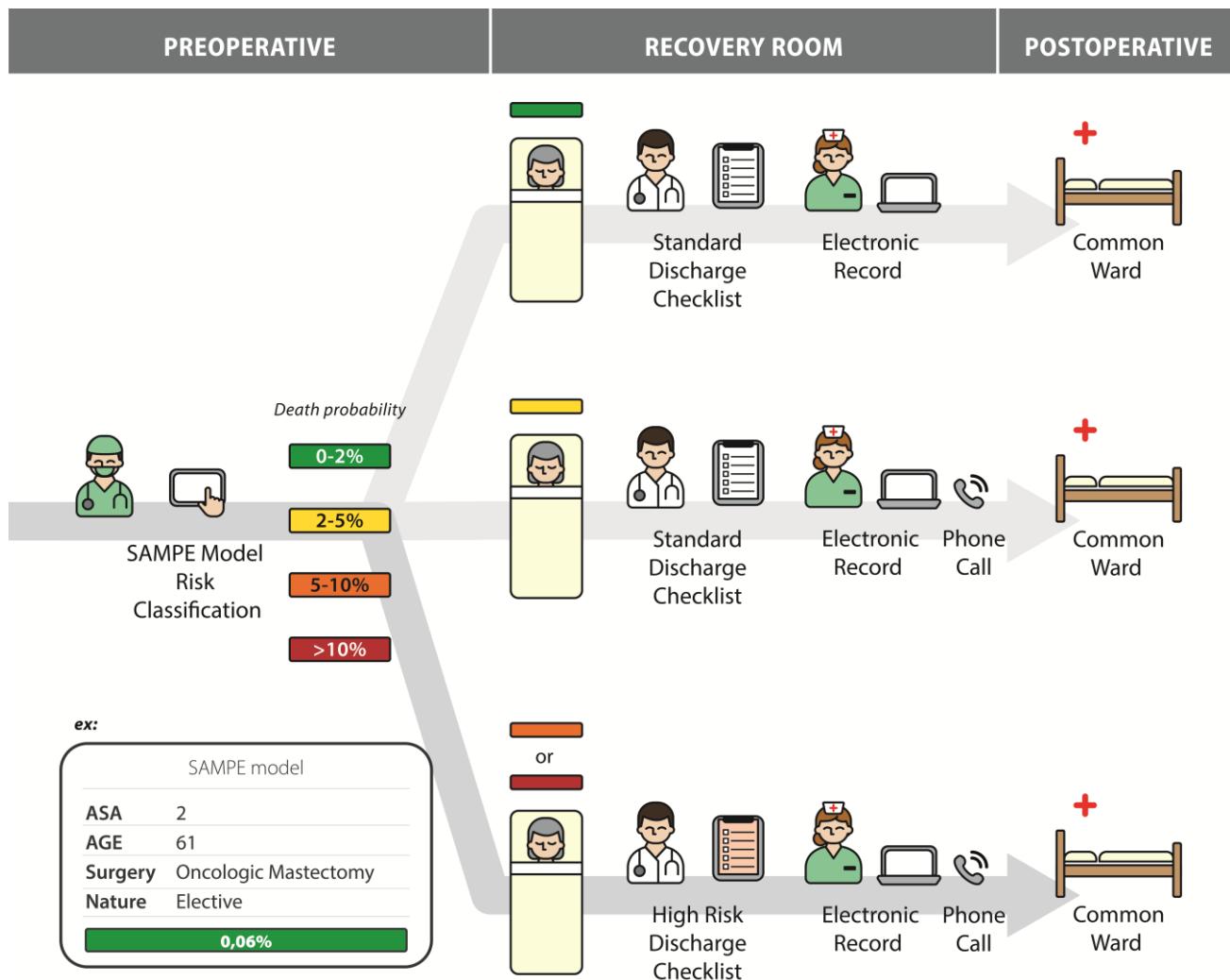
- [1] Shah N, Hamilton M. Clinical review: Can we predict which patients are at risk of complications following surgery? *Crit Care* 2013;17:226. doi:10.1186/cc11904.
- [2] Sankar A, Beattie WS, Wijeysundera DN. How can we identify the high-risk patient? *Curr Opin Crit Care* 2015;21:328–35. doi:10.1097/MCC.0000000000000216.
- [3] Cohen MD, Hilligoss PB. The published literature on handoffs in hospitals: deficiencies identified in an extensive review. *Qual Saf Health Care* 2010;19:493–7. doi:10.1136/qshc.2009.033480.
- [4] Biccard BM, Madiba TE, Kluyts H-L, Munlemvo DM, Madzimbamuto FD, Basenero A, et al. Perioperative patient outcomes in the African Surgical Outcomes Study: a 7-day prospective observational cohort study. *Lancet* 2018;391:1589–98. doi:10.1016/S0140-6736(18)30001-1.
- [5] Stephens TJ, Peden CJ, Pearse RM, Shaw SE, Abbott TEF, Jones EL, et al. Improving care at scale: process evaluation of a multi-component quality improvement intervention to reduce mortality after emergency abdominal surgery (EPOCH trial). *Implement Sci* 2018;13:142. doi:10.1186/s13012-018-0823-9.
- [6] Ahmad T, Bouwman RA, Grigoras I, Aldecoa C, Hofer C, Hoeft A, et al. Use of failure-to-rescue to identify international variation in postoperative care in low-, middle- and high-income countries: a 7-day cohort study of elective surgery. *Br J Anaesth* 2017;119:258–66. doi:10.1093/bja/aex185.
- [7] Barnett S, Moonesinghe SR. Clinical risk scores to guide perioperative management. *Postgrad Med J* 2011;87:535–41. doi:10.1136/pgmj.2010.107169.
- [8] Stefani LC, Gutierrez CDS, Castro SM de J, Zimmer RL, Diehl FP, Meyer LE, et al. Derivation and validation of a preoperative risk model for postoperative

- mortality (SAMPE model): An approach to care stratification. PLOS ONE 2017;12:e0187122. doi:10.1371/journal.pone.0187122.
- [9] Langley GJ, Moen RD, Nolan KM, Nolan TW, Norman CL, Provost LP. The Improvement Guide: A Practical Approach to Enhancing Organizational Performance. John Wiley & Sons; 2009.
- [10] Boehm O, Baumgarten G, Hoeft A. Epidemiology of the high-risk population: perioperative risk and mortality after surgery. Curr Opin Crit Care 2015;21:322–7. doi:10.1097/MCC.0000000000000221.
- [11] Stefani LC, Gamermann PW, Backof A, Guollo F, Borges RMJ, Martin A, et al. Perioperative mortality related to anesthesia within 48 h and up to 30 days following surgery: A retrospective cohort study of 11,562 anesthetic procedures. J Clin Anesth 2018;49:79–86. doi:10.1016/j.jclinane.2018.06.025.
- [12] Whitlock EL, Feiner JR, Chen L-L. Perioperative Mortality, 2010 to 2014: A Retrospective Cohort Study Using the National Anesthesia Clinical Outcomes Registry. Anesthesiology 2015;123:1312–21. doi:10.1097/ALN.0000000000000882.
- [13] Pearse RM, Moreno RP, Bauer P, Pelosi P, Metnitz P, Spies C, et al. Mortality after surgery in Europe: a 7 day cohort study. Lancet 2012;380:1059–65. doi:10.1016/S0140-6736(12)61148-9.
- [14] Bainbridge D, Martin J, Arango M, Cheng D, Evidence-based Peri-operative Clinical Outcomes Research (EPiCOR) Group. Perioperative and anaesthetic-related mortality in developed and developing countries: a systematic review and meta-analysis. Lancet 2012;380:1075–81. doi:10.1016/S0140-6736(12)60990-8.

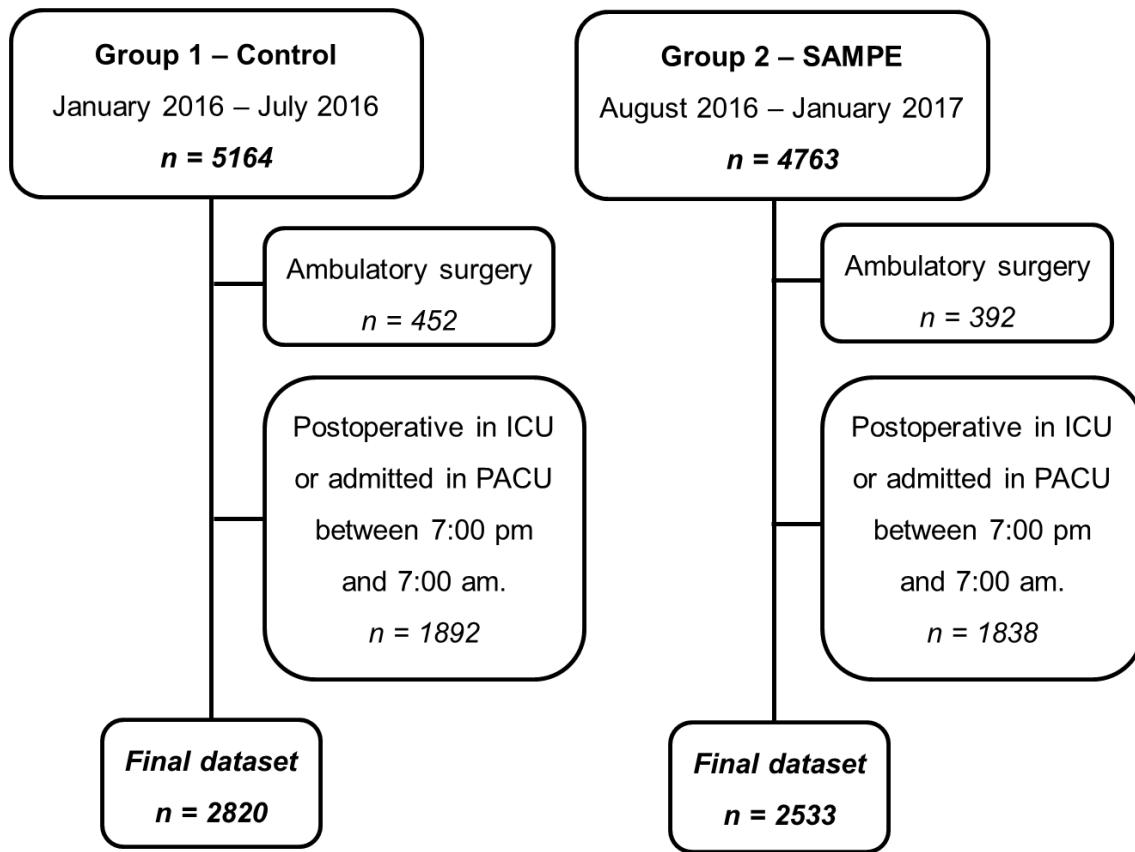
- [15] Moonesinghe SR, Mythen MG, Grocott MPW. High-risk surgery: epidemiology and outcomes. *Anesth Analg* 2011;112:891–901. doi:10.1213/ANE.0b013e3181e1655b.
- [16] Ghaferi AA, Birkmeyer JD, Dimick JB. Variation in hospital mortality associated with inpatient surgery. *N Engl J Med* 2009;361:1368–75. doi:10.1056/NEJMsa0903048.
- [17] Ghaferi AA, Dimick JB. Importance of teamwork, communication and culture on failure-to-rescue in the elderly. *Br J Surg* 2016;103:e47-51. doi:10.1002/bjs.10031.
- [18] White K, Scott IA, Vaux A, Sullivan CM. Rapid response teams in adult hospitals: time for another look? *Intern Med J* 2015;45:1211–20. doi:10.1111/imj.12845.
- [19] Petersen Tym MK, Ludbrook GL, Flabouris A, Seglenieks R, Painter TW. Developing models to predict early postoperative patient deterioration and adverse events. *ANZ J Surg* 2017;87:457–61. doi:10.1111/ans.13874.
- [20] Taenzer AH, Pyke JB, McGrath SP. A review of current and emerging approaches to address failure-to-rescue. *Anesthesiology* 2011;115:421–31. doi:10.1097/ALN.0b013e318219d633.
- [21] Moons KGM, Altman DG, Vergouwe Y, Royston P. Prognosis and prognostic research: application and impact of prognostic models in clinical practice. *BMJ* 2009;338:b606. doi:10.1136/bmj.b606.
- [22] Altman DG, Vergouwe Y, Royston P, Moons KGM. Prognosis and prognostic research: validating a prognostic model. *BMJ* 2009;338:b605. doi:10.1136/bmj.b605.
- [23] Peden CJ, Moonesinghe SR. Measurement for improvement in anaesthesia and intensive care. *Br J Anaesth* 2016;117:145–8. doi:10.1093/bja/aew105.

- [24] Peden CJ, Stephens T, Martin G, Kahan BC, Thomson A, Rivett K, et al. Effectiveness of a national quality improvement programme to improve survival after emergency abdominal surgery (EPOCH): a stepped-wedge cluster-randomised trial. *Lancet* 2019;393:2213–21. doi:10.1016/S0140-6736(18)32521-2.
- [25] Stiegler MP, Tung A. Cognitive processes in anesthesiology decision making. *Anesthesiology* 2014;120:204–17. doi:10.1097/ALN.0000000000000073.
- [26] Wijeysundera DN. Predicting outcomes: Is there utility in risk scores? *Can J Anaesth* 2016;63:148–58. doi:10.1007/s12630-015-0537-2.
- [27] Patel S, Gillon SA, Jones DA. Rapid response systems: recognition and rescue of the deteriorating hospital patient. *Br J Hosp Med (Lond)* 2017;78:143–8. doi:10.12968/hmed.2017.78.3.143.
- [28] Johnston M, Arora S, King D, Stroman L, Darzi A. Escalation of care and failure to rescue: a multicenter, multiprofessional qualitative study. *Surgery* 2014;155:989–94. doi:10.1016/j.surg.2014.01.016.
- [29] Glance LG, Osler T, Li Y, Lustik SJ, Eaton MP, Dutton RP, et al. Outcomes are Worse in US Patients Undergoing Surgery on Weekends Compared With Weekdays. *Med Care* 2016;54:608–15. doi:10.1097/MLR.0000000000000532.
- [30] Kork F, Spies C, Conrad T, Weiss B, Roenneberg T, Wernecke K-D, et al. Associations of postoperative mortality with the time of day, week and year. *Anaesthesia* 2018;73:711–8. doi:10.1111/anae.14228.
- [31] Glance LG, Osler TM, Neuman MD. Redesigning surgical decision making for high-risk patients. *N Engl J Med* 2014;370:1379–81. doi:10.1056/NEJMp1315538.
- [32] Grocott MPW, Plumb JOM, Edwards M, Fecher-Jones I, Levett DZH. Redesigning the pathway to surgery: better care and added value. *Perioper Med (Lond)* 2017;6:9. doi:10.1186/s13741-017-0065-4.

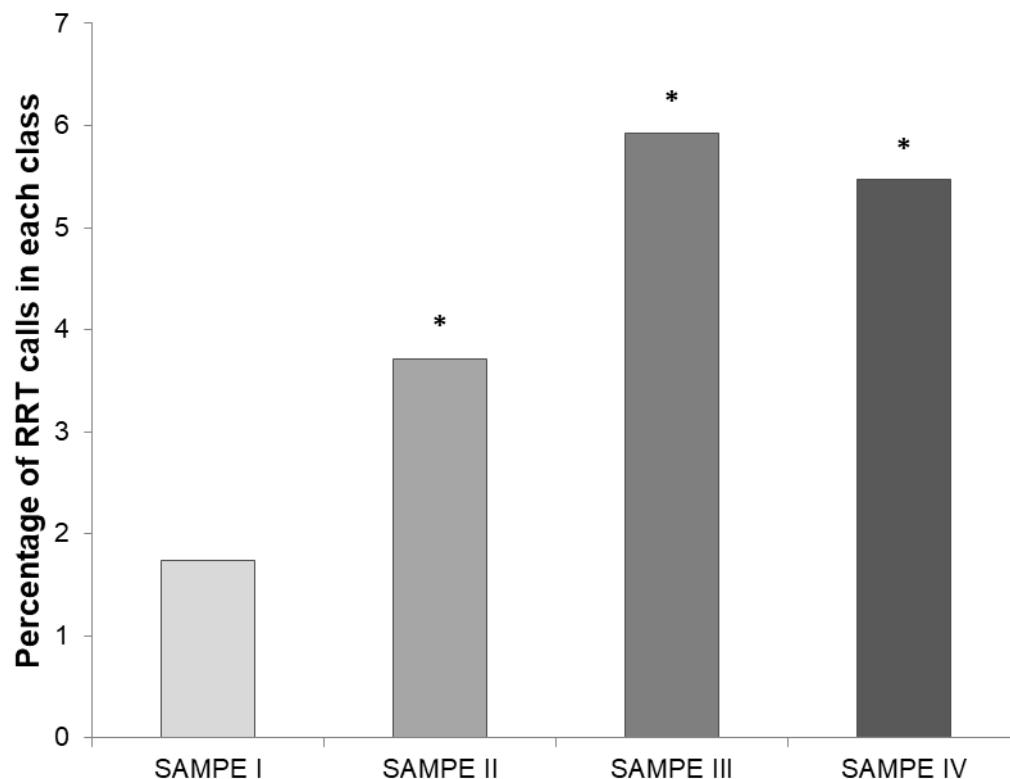
- [33] Grocott MPW, Edwards M, Mythen MG, Aronson S. Peri-operative care pathways: re-engineering care to achieve the “triple aim.” *Anaesthesia* 2019;74 Suppl 1:90–9. doi:10.1111/anae.14513.



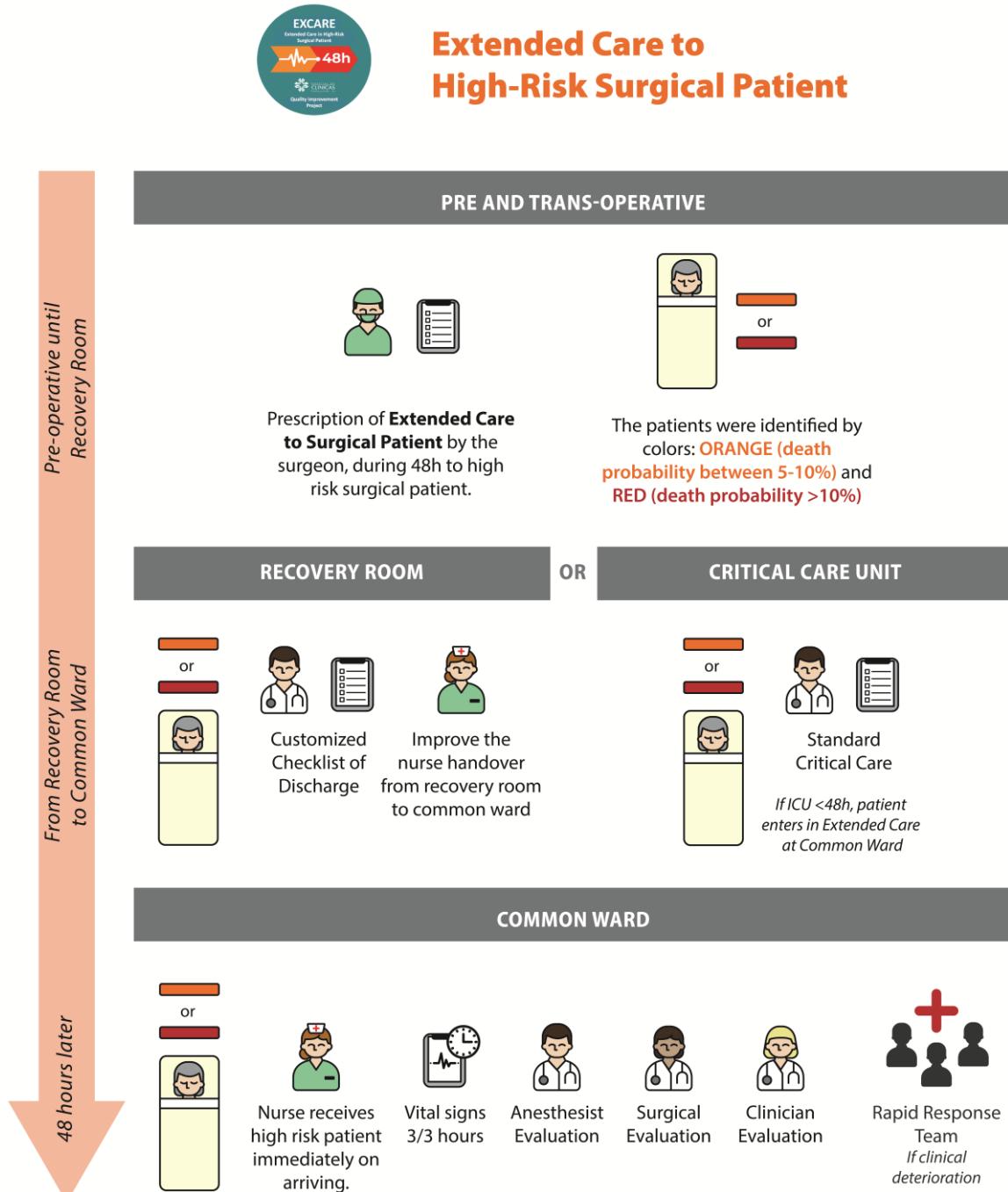
**Fig. 1.** Schematic representation of the care flow of surgical patients after implementation of the SAMPE Model.



**Fig. 2.** Trial diagram for the analysis of the SAMPE Model implementation dataset.



**Fig. 3.** Percentage of RRT calls according to SAMPE risk class. \* indicates a statistically significant difference ( $p < 0.05$ ) in comparison with Risk Class I.



**Fig. 4.** Schematic representation of the care flow of high-risk surgical patients (ExCare pathway).

**Table 1.** Characteristics of Group 1 (control) and Group 2 (intervention).

	<b>Control Group (n= 2820)</b>	<b>Intervention Group (n=2533)</b>
<b>Age (years), mean ± SD</b>	54.02 ± 16.67	53.91 ± 16.57
<b>Age (years)</b>		
16 - 35	450 (16%)	418 (16.5%)
36 - 55	931 (33%)	845 (33.4%)
56 - 75	1178 (41.8%)	1048 (41.4%)
> 76	261 (9.3%)	221 (8.7%)
<b>Gender</b>		
Male	1178 (41.8%)	1061 (41.9%)
Female	1642 (58.2%)	1472 (58.1%)
<b>ASA Physical Status</b>		
1	556 (19.7%)	462 (18.2%)
2	1616 (57.3%)	1451 (57.3%)
3	624 (22.1%)	590 (23.3%)
4	24 (0.9%)	30 (1.2%)
<b>Surgery type</b>		
Elective	2246 (79.6%)	2095 (82.7%)
Emergency	574 (20.4%)	438 (17.3%)
<b>Surgical severity</b>		
Minor	822 (29.1%)	820 (32.4%)
Intermediate	1270 (45%)	1103 (43.5%)
Major	728 (25.8%)	610 (24.1%)
<b>SAMPE risk class</b>		
I	2181 (77.3%)	1938 (76.5%)
II	270 (9.5%)	269 (10.6%)
III	225 (7.9%)	196 (7.7%)
IV	144 (5.1%)	130 (5.1%)

<b>Surgical specialty</b>		
General and digestive surgery	396 (14.0%)	333 (13.14%)
Vascular	256 (9.07%)	188 (7.42%)
Urology	442 (15.67%)	476 (18.79%)
Orthopaedics	310 (10.99%)	300 (11.84%)
Neurosurgery and spinal	62 (2.19%)	52 (2.05%)
Gynaecology and breast surgery	288 (10.21%)	252 (9.94%)
Colorectal	105 (3.72%)	90 (3.55%)
Upper gastrointestinal and hepatobiliary	585 (20.74%)	501 (19.77%)
Thoracic surgery	105 (3.72%)	78 (3.07%)
Ear, nose and throat	210 (7.44%)	197 (7.77%)
Plastic surgery	46 (1.63%)	46 (1.81%)
Maxillofacial	15 (0.53%)	20 (0.78%)

**Table 2.** Rapid Response Team calls at 30 postoperative days.

<b>SAMPE class</b>	<b>Total Sample</b>		<b>Control Group</b>		<b>Intervention Group</b>		<i>P</i> value*
	Overall	RRT call	Overall	RRT call	Overall	RRT call	
<b>I</b>	4119	102 (2.47%)	2181	47 (2.15%)	1938	55 (2.84%)	0.16
<b>II</b>	539	37 (6.86%)	270	12 (4.44%)	269	25 (9.29%)	0.02
<b>III</b>	421	42 (9.97%)	225	25 (11.11%)	196	17 (8.67%)	0.40
<b>IV</b>	274	53 (19.34%)	144	34 (23.61%)	130	19 (14.62%)	0.05
<b>Total</b>	5353	234 (4.37%)	2820	118 (4.18%)	2533	116 (4.57%)	0.60

RRT, Rapid Response Team.

**Table 3.** Mortality by SAMPE Model risk class.

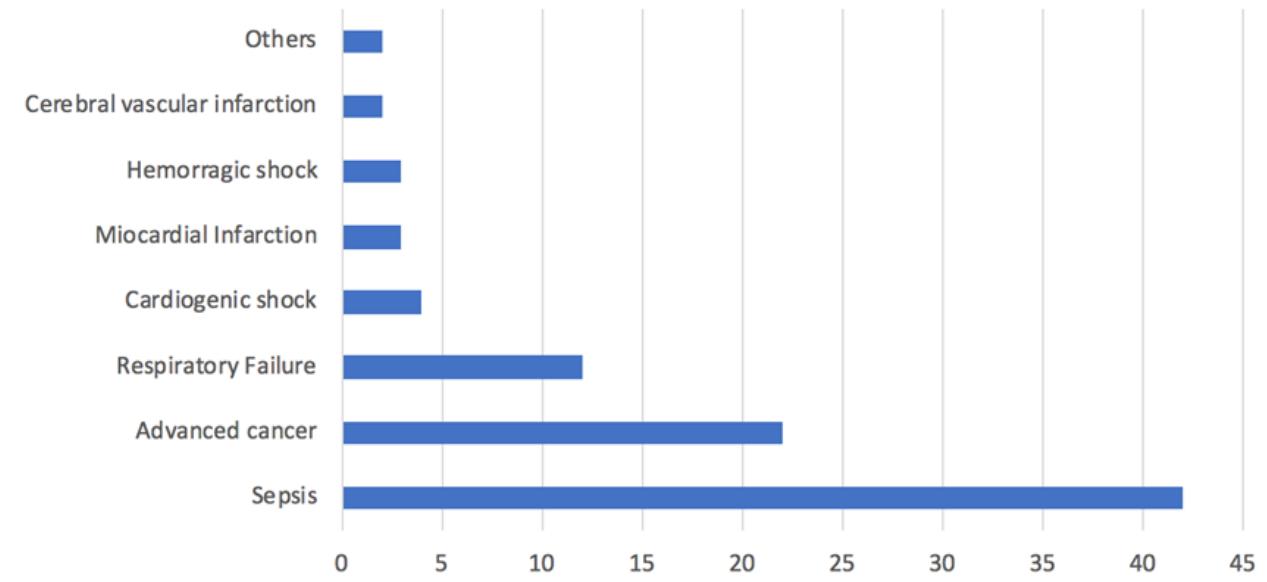
<b>SAMPE risk class</b>	<b>Total sample</b>	<b>Deaths</b>	<b>% deaths within total sample</b>	<b>% within deaths</b>
<b>I</b>	4119	15	0.4%	16.7%
<b>II</b>	540	16	3%	17.8%
<b>III</b>	403	17	4%	18.9%
<b>IV</b>	274	42	15.3%	46.7%

## Supplementary Material

**Table S1.** Standard PACU checklist discharge criteria.

Standard PACU discharge checklist (all criteria must be present at discharge)
(    ) Stable vital signs
(    ) Awake, with preoperative sensory pattern
(    ) $\text{SPO}_2 > 90\%$
(    ) Pain control
(    ) Absence of nausea and vomiting
(    ) Absence of surgical bleeding
(    ) Absence of motor block secondary to regional anaesthesia (or motor block in regression)

PACU, Post-Anaesthetic Care Unit.



**Fig. S1:** Frequencies of death causes (n = 90).

STROBE Statement—Checklist of items that should be included in reports of *cohort studies*

	<b>Item No</b>	<b>Recommendation</b>	<b>Page</b>
<b>Title and abstract</b>	1	(a) Indicate the study's design with a commonly used term in the title or the abstract	110-112
		(b) Provide in the abstract an informative and balanced summary of what was done and what was found	112
<b>Introduction</b>			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	114
Objectives	3	State specific objectives, including any prespecified hypotheses	115
<b>Methods</b>			
Study design	4	Present key elements of study design early in the paper	116
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	116
Participants	6	(a) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	116-117
		(b) For matched studies, give matching criteria and number of exposed and unexposed	116
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	116;118
Data sources/measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	116-118
Bias	9	Describe any efforts to address potential sources of bias	NA
Study size	10	Explain how the study size was arrived at	118
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	116-118
Statistical methods	12	(a) Describe all statistical methods, including those used to control for confounding	119
		(b) Describe any methods used to examine subgroups and interactions	119
		(c) Explain how missing data were addressed	NA
		(d) If applicable, explain how loss to follow-up was addressed	NA
		(e) Describe any sensitivity analyses	NA
<b>Results</b>			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	120
		(b) Give reasons for non-participation at each stage	120
		(c) Consider use of a flow diagram	134
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	137
		(b) Indicate number of participants with missing data for each variable of	NA

		interest	
		(c) Summarise follow-up time (eg, average and total amount)	120-121
Outcome data	15*	Report numbers of outcome events or summary measures over time	121
Main results	16	(a) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	120-121
		(b) Report category boundaries when continuous variables were categorized	120-121
		(c) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	NA
<b>Discussion</b>			
Key results	18	Summarise key results with reference to study objectives	122
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	122-126
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	122-126
Generalisability	21	Discuss the generalisability (external validity) of the study results	124
<b>Other information</b>			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	111

\*Give information separately for exposed and unexposed groups.

**Note:** An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at <http://www.plosmedicine.org/>, Annals of Internal Medicine at <http://www.annals.org/>, and Epidemiology at <http://www.epidem.com/>). Information on the STROBE Initiative is available at <http://www.strobe-statement.org>.

7.4 ARTIGO 4 - THE HIGH-RISK SURGICAL PATIENT HIGHLIGHTED:  
VALIDATION OF A LEAN AND ACCURATE PREDICTIVE MODEL OF  
POSTOPERATIVE DEATH IN A COHORT OF 16.618 PATIENTS: THE  
SAMPE II MODEL

**Anaesthesia****Original Article**

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**The high-risk surgical patient highlighted: validation of a lean and accurate predictive model of postoperative death in a cohort of 16 662 patients: The SAMPE II model**

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Keywords: risk assessment; risk stratification; prognostic models; postoperative mortality.

**Short title:**

SAMPE II model: a predictive model of postoperative death

## Summary

We sought to validate a preoperative instrument to predict postoperative mortality in a cohort of 16 618 patients submitted to non-cardiac surgical procedures. We assessed the performance of the new model (SAMPE II) which comprised pre-selected variables (age, ASA physical status, surgical severity and surgical nature-urgent or elective) using measures of discrimination, calibration and association.

SAMPE II model was well calibrated assessed using the Hosmer–Lemeshow test (9.26; p= 0.41). All variables were significant for the outcome postoperative death: ASA physical status (OR 6.66; CI 5.65-7.84), major vs non-major surgery (OR 1. 69; CI 1.35-2.13), status non-elective vs elective (OR 4.25; CI 3.36-5.37) and age, which was modelled using restricted cubic splines, showed progressive significance above 70 years. Also, the discrimination by statistic C analysis (AUROC) was excellent 0.926, (CI 0.91-0.93) and the changes in risk category favoured the SAMPE II, since more patients who died moved up to a higher risk category than those who have gone downward. Cox proportional model with SAMPE risk classes as predictors of postoperative death showed a significant increase in the estimated hazard ratio (HR) with the rise in risk classes; HR class II vs class I was 3.61 (CI 2.50-5.23), HR of class III vs class I was 5.54 (3.76-8.19) and HR of class III vs class I was 21.78 (CI 16.06-29.54).

The SAMPE II model is a robust instrument to identify the high-risk surgical patient. This model could ground the implementation of multiprofessional, risk-reduction strategies during the perioperative patient's journey.

## Introduction

Whilst the postoperative recovery is uncomplicated in the majority of the cases, a small proportion of high-risk surgical patients are prone to complications that have negative impact on rehabilitation, consume a disproportional share of resources and are responsible for higher perioperative mortality rates. Accurate and timely identification of high-risk patients is strongly recommended by guidelines on the preoperative assessment [1–4]. Thus, in the last decade we have seen a great evolution towards accurate personalized predictions models of perioperative outcomes. These models should be used to guide perioperative interventions intended to reduce complications, inform patient and family about expected risks and arrange for appropriate levels of postoperative care [2]. However, models performance across different world regions is largely unknown and extrapolation of risk prediction should be done with caution, considering the singularities of the different Health Systems.

In a recent article [5] we could demonstrate the accuracy of a new preoperative risk assessment tool, the SAMPE (Anesthesia and Perioperative Medicine Service) model. It was designed to incorporate characteristics of an ideal risk model: it is easily implemented by the bedside; it is composed by few and sustainable variables including clinical data from the patient and from the procedure itself (age; ASA physical status classification - American Society of Anesthesiologists; surgical severity - minor, intermediate or major; and surgical nature - urgent or elective). The first version of this model had a high discriminative power toward the outcome of in-hospital mortality up to 30 days.

Meanwhile, it is essential to cautiously analyse any new tool to include in

clinical care. Therefore, the efforts related to the continuous evaluation of the measurement are essential to provide a reliable instrument [6,7]. Since intermediate surgical severity was not different from the minor one, we decided to refine the first version of the SAMPE model, unifying the minor and intermediate procedure severities. Also, the variable age was revisited through a modern statistical approach with splines, in order to increase the reliability of age impact on the risk model above mentioned.

Thus, the primary aim of this study was to validate a risk model of postoperative mortality (SAMPE II) based on the first version of SAMPE model and to determine its overall performance. We hypothesize that it will result in an improved mortality prediction model relative to the original one in a new sample of general surgical patients above sixteen years of age.

## **Methods**

### *Hospital setting, procedures and patients*

The study was conducted in an academic, quaternary care centre in the South of Brazil. Ethical approval was provided by the Ethical Committee for Postgraduate and Research Group from Hospital de Clínicas de Porto Alegre (HCPA) - Brazil (project number 2016-0229). HCPA acts as a quaternary university hospital that serves a population of approximately four million people in the southern Brazil. Data from all consecutive surgical procedures, performed in patients above 16 years of age, at HCPA from January 1, 2016 to December 31, 2018 were included. Patients were followed until 30 days after surgery, even if they remained in hospital for longer. The final derivation study cohort consisted of 16 618 patients.

Written informed consent was not required and a confidentiality agreement to access information from institution database was assigned.

*Original SAMPE Model variables prediction algorithm*

The purpose of the original SAMPE model [5], compounded by four preoperative variables easily collected at bedside was kept, and a new regression logistic model was fitted using the same predictors variables: ASA physical status (PS), surgical severity (major, intermediate and minor), surgical nature (elective or urgent) and age. The binary outcome was postoperative in-hospital death up to 30 days. Goodness-of-fit was than assessed by the Hosmer–Lemeshow test which compares observed and predicted risk across the range of predicted risk, with non-significant chi-square test results ( $p > 0.05$ ) indicating a well-calibrated model. After the initial result with the original variables, sequential adjustments were done and a final model with new coefficients was obtained being its performance metrics compared to the original model.

*Variables Adjustments of SAMPE 2 model*

Surgical Severity Grouping: In the construction of the original model, in order to define surgical severity, we grouped 1200 current terminology codes for similar procedures into subtypes (e.g., bile duct surgery, pulmonary resection). Then, we classified these procedures into major, intermediate, or minor degree, using a categorization scheme based on literature review [8,9] and expert opinions, who considered surgical time, trauma, and predicted bleeding. Meanwhile, the coefficient for the intermediate risk surgeries in relation to the minor was not significant both in the new sample as well as in the original derivation sample [5]. Thus, an analysis of SAMPE model predictive performance with the adjustment of the variable surgical severity, combining the two categories (minor and intermediate severity) was done, being the surgical procedures classified into two groups: non-major and major severity.

Age and the new polynomial regression splines: Age is an independent predictor of thirty-day mortality and complication after nonemergent general surgeries. Individuals aged 80 and older have especially high mortality after renal, cardiovascular, and pulmonary complications [8]. As a continuous predictor it is necessary to identify its linearity. The adjustment of the surgical severity leads to a non-linear course of the variable age. Therefore we decided to deal with age in a more elaborate form such as using polynomial regression splines [9]. Restricted cubic splines allow for great flexibility in the form of the relationship between predictor and outcome. Spline regression includes a continuous exposure coded by using spline functions, i.e. piecewise functions whose ‘pieces’ are polynomials (splines) of low degrees defined over adjacent intervals. The junction between two intervals is called “knot” [10]. We have modelled age using restricted cubic splines with five knots to allow for non-linearity.

Other variables: The nature of the procedure (urgent or elective) enter in the information system at the time of the surgery appointment. During the surgical description the surgeon enters the ASA classification according the anaesthesiologist record. The hospital information system also contains the patient’s status at hospital discharge or at 30 days after surgery, which was used for the endpoint definition.

#### *Statistical analysis*

With logistic regression, we developed a continuous risk estimating equation with the pre-selected variables from original SAMPE model.

Multivariable logistic regression models were fitted with adjusted variables in the sample of 16 618 patients. Age, the sole continuous variable was modelled using restricted cubic spline functions to allow for non-linearity. We

assessed the performance of both the original and the new model using a variety of methods, including traditional ones and some new refined measures. First, we evaluated the calibration, which refers to the agreement between observed outcomes and predictions by the Hosmer-Lameshow statistics, where the higher the p value was, the better the calibration of the model. Also, the overall performance of the new SAMPE 2 was checked with the Brier score. This score simultaneously addresses calibration, the statistical consistency between the predicted probability and the observations as well as sharpness, which refers to the concentration of the predictive distribution. Being mainly a relative measure, a lower score points to a superior model; it can range from 0 for a perfect model to 0.25 for a non-informative model with a 50% incidence of the outcome [11].

Second, we compared the traditional performance measure of concordance (c) statistic of the original SAMPE model to the updated SAMPE II using the change in the area under the receiver operating characteristic curve (AUC).

We also undertook a Cox proportional hazards modelling in which the dependent variable was in hospital death. The independent variable was the risk class on the SAMPE model. The risk classes were considered the independent predictors of the primary outcome and we determined the adjusted hazard ratio and the associated 95% confidence intervals for each risk class.

Third, we calculated reclassification of risk among patients who experienced the outcome and separately among patients who did not experience the primary outcome to determine if the adjustments in the original model improved risk classification. Any upward movement in risk categories for subjects who died implies improved classification, and any downward

movement indicates worse reclassification [12]. The opposite interpretation applies to subjects without the outcome. Categorical Net Reclassification Improvement (NRI) quantifies the improvement in reclassification. It is calculated by the sum of differences in proportions of individuals moving up minus the proportion moving down for those with the outcome, and the proportion of individuals moving down minus the proportion moving up for those without the outcome [13]. The NRI was calculated to the four risk categories of postoperative death probability according the SAMPE model. All analyses were performed using R version 3.1.1 and SAS software version 9.4. A two-tailed p value < 0.05 denoted statistical significance.

## Results

During the 24 months of analysis, 16 618 patients comprised the dataset used to develop the SAMPE 2 model. We excluded those who received only local anaesthesia by the surgeon or whose procedures were diagnostic rather than therapeutic. Also, when more than one surgical procedure was performed during the same hospital admission, only the major procedure was taken into account for analysis. The patient (not the operation) was the unit of analysis. Patients with erroneously duplicated or missing data were excluded, and only patients with complete predictor variables were included for analysis. In this series, there were 465 postoperative deaths (2.80%). Table 1 describes the characteristics of the overall sample and of the 30-day in-hospital postoperative deaths, stratified by the clinical and surgical variables of interest. The majority of patients had urologic, digestive or general surgical procedures, were ASA II, between 56-75 years of age, submitted to elective surgeries (79.8%). On the other hand, the patients who died were mostly ASA IV (40%), submitted to urgent surgeries (71.6%) of digestive or general specialty.

### *The Original SAMPE model in the new sample*

Multivariable logistic regression model was fitted with the original pre-selected variables: age, ASA, nature of procedure (elective vs non-elective), and procedure degree (major, intermediate, or minor) in the new sample of 16 618 patients. The odds ratios (OR) were very similar to the original sample from patients which had surgery in 2012-2013 at the same institution. The intermediate versus minor procedure was not different, and even the intermediate was protective in relation to minor procedure. This is not intuitive for practical use. Also, the increase in risk according to age, in spite of the linearity assumption, should be viewed with caution. The model was quite accurate (C Statistic 0.927 – CI 0.91- 0.03), but the Hosmer Lemeshow test, the statistical test for goodness of fit showed poor overall calibration of the model (Chi-square: 16.69; p= 0.0334). Table 2 lists the variables entered into the model and their respective weights (odds ratios and confidence intervals).

### *The SAMPE II model results*

Variables adjustments were sequentially done to build a more consistent model. Since intermediate vs minor procedures had no difference in the original model, they were classified into major vs non-major, to deal with the inconsistency of three severities categories of the original model. This simplified the great variability of procedures classification. Yet the variable age showed a non-linear distribution, and, to avoid categorization, it entered in the model with adjusted splines. A spline is a smoothed curve included in a regression model, in which the range of values is split up with knots defining the end of one segment and the starting of the next [14]. Figure 1 shows the Odds of death as a function of age, using restricted cubic splines with five

knots - orange curve, in comparison with the linear curve (blue), holding all other variables constant at representative levels.

In order to compute OR after fitting the model including splines we compare specific ages with the single reference age of 17 years. For instance, the OR of in-hospital death after a surgery in a 70 years-old patient is 2.70 higher than the 17 years patient. The coefficients of the new model are presented in Table 3.

#### *SAMPE II Performance and Reclassification Results*

The performance of the SAMPE II model was assessed by measures of discrimination (C statistic) and calibration (calibration curve Hosmer-Lameshow statistic). When the procedures were categorized in major or non-major and age was analysed with splines, the SAMPE risk model improved in discrimination, in spite of the little change in C statistical (AUROC 0.926, 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 the excellent overall performance of the model.

The Hazard Ratio point estimates for each SAMPE class category as showed in Table 4 confirmed a progressive increase in risk of death with increasing in the SAMPE risk class (being risk class I the index).

The clinical impact of the improvement in the model, achieved by upgrading the variables, can be assessed by means of identifying changes in classification categories when the new model is applied in the group who had the primary outcome (30-day death). Among patients who had died, the reassignment occurred in 26 patients (5.59%), being 65% of these reassigned to a higher category. Among the survivors there were 477 reassessments (2.8%), being 63% to a lower risk category. Therefore, reassessments are

considered appropriate when more patients with the outcome are classified in a higher risk group rather than a lower one [13]. We also calculated the NRI [15] to quantify the net improvement of SAMPE II versus the original one, by placing patients into the appropriate category (more deaths into a higher category, more survivors into a lower category). The categorical NRI was 0.025 (0.0035 - 0.0467),  $p = 0.0229$ , and there was a 2.5% improvement in general classification.

## **Discussion**

In this cohort study with more than 16 000 patients we validated a lean and effective preoperative risk model based on four clinical and surgical variables, in order to stratify adult patients into risk classes of in-hospital probability of postoperative death.

We presented an updated version of the original SAMPE model, based in preoperative variables easily collected, namely age, surgical severity (major vs non-major), ASA classification, and nature of the procedure (elective vs urgent). We examined the performance of the model with updated variables, simplifying the surgical procedures categorization into major vs non-major complexity. Also, the variable age was statistically refined with splines which allowed the identification of risk progression with advancing age, in a nonlinear, more realistic way. All these adjustments provided a better performance of our proposed preoperative risk tool.

### *SAMPE 2 model compared to other risk models*

The main finding of our study was the confirmation of our risk model ability to identify the high-risk surgical patient with an easily and robust instrument. A supplemental method to enhance the subjective clinical prediction could influence the type of operation performed, improve the patient information,

and, mostly, could guide the complexity of postoperative care. Therefore, in an effort to optimize risk prediction, our proposed model incorporates modern statistical approach and a simplified, plausible selection of variables that are intuitively linked to higher risk. It is improbable that a more complex model, with more or different variables could change the risk approach, since the performance of the model is excellent, in more than one large sample. Furthermore, considering the law of parsimony, if a pre-selected combination of variables can explain a phenomenon with the same level of accuracy as a more complex model, the simple one should be preferred [16].

Some models incorporated variables similar to ours [17–19]. The SORT model [17], from the United Kingdom, used the ASA classification, the surgical nature, specialty, severity, cancer and age to compound the model. Also, the Surgical Mortality Probability Model (SMP-M) based on a cohort of ACS NSIQP with more than 200 centres, incorporates just three variables: surgical severity, ASA and surgical nature and exhibits very good discrimination toward the outcome in-hospital death [18]. With our study we confirmed the plausibility that the strength of the model is grounded in the combination of data from patient and from the procedure. The advantage of our model is that age, which is a variable that encompass the burden of physiologic reserve [20,21], is properly valued, with splines approach that enriches our result. In the SAMPE II model individuals above 70 years-old have progressive, significant increase in the probability of death result. Likewise, surgical severity with dichotomic division facilitates the comprehension of the final user since the division in several strata is not intuitive and is far from consensual between physicians, managers, and countries.

*Strengths and limitations of our study*

We can highlight some methodological strengths in our study. We analysed a large number of patients with a wide spectrum of clinical and surgical risk. The variables which compound the model are intrinsic to the preoperative evaluation, hence the risk classification is easily achieved and provides complementary objective information that reduces the subjectivity of physician perception.

To validate the model we assessed its performance using traditional (C-Statistic, Hosmer-Lameshow) and novel measures (Brier score and NRI). C statistic, the classical discrimination measure, of the new model was excellent (0.926; CI 0.91-0.93), but no different from the original SAMPE model. Since the ROC curve and C-statistic are insensitive in assessing the impact of adding new predictors to a predictive model, it is essential to analyse the performance of a model beyond the ROC curve. To have an impact the OR from individual predictor needs to be sizeable and small changes in the variables are unlikely to produce significant changes in ROC curve [22,23]. To overcome this limitation we used other measures. The Brier score result adds information about probabilistic prediction, takes on a value between 0 and 1, being the lower score associated to better predictions calibration. The square root of the Brier score is thus the expected distance between the observed and predicted value on the probability scale [12,24]. The overall good performance of the new model was verified by the reduction in Brier score result (0.034 for original SAMPE vs 0.019 for SAMPE II).

Besides, the improve in calibration, which is the ability to correctly estimate the risk or probability of a future event, was confirmed with the most popular measure of calibration, the Hosmer-Lameshow goodness of fit test. This test is a measure of how well the model fits the data. The Pearson chi-squared

goodness of fit test provides a method to test if the observed and expected proportions differ significantly. The new model showed better adjustment through lower result with less significance ( $HL = 9.26; p = 0.41$ ), when compared to the original one applied to the same population ( $HL = 16.69; p = 0.0334$ ). As with the classic goodness-of-fit tests, low p values suggest rejection of the model.

We also analysed the changes in risk category, to show how many subjects were reclassified by the new model in comparison to the original one. Overall, we had few reassessments (8.4% of patients had their risk category changed), which is good. The clinical improvement in the model was assessed by identifying more positive than negative changes in classification categories. Among the 465 patients who had died, reassessments occurred in 26 of them, being 65% of these to a higher category. The NRI confirmed that patients who died moved up to a higher risk category in a higher proportion than those who have gone downward [12,15].

Beyond that performance measures, we also confirmed the magnitude of class effect using the risk classes as predictors of death in a COX proportional model. Considering the class I (probability of death less than 2%) as reference we found a progressive and significant increase in the estimated hazard ratio as long as risk class rises. This information is useful for practical communication. For example, we can share our concern with the family of a particular patient, classified as SAMPE risk class III (between 5-10% of probability of death), presenting a more understandable argument: "as your relative is above 70, he will be submitted to a major, elective procedure, and has several comorbidities (ASA 3), the chance of his dying in the postoperative period is 8 times higher than a healthy subject."

There were also some limitations in our study. First, the model reflects mortality risk in the patient population of a single institution and cannot yet be generalized to other care settings or geographic locations. Nevertheless, our mortality rate did not differ greatly from rates reported in developed countries. The overall in-hospital mortality of our sample (2.8%) was comparable to the overall mortality in a 7-day European cohort study [25]. Second, two of the four variables included in the model, the ASA classification and the surgical severity, could be considered subjective measures. To reduce the inter user variability we developed a digital interface where the ASA classification with detailed examples appeared on the screen at each use [26]. Also, regarding the procedures severity classification, the electronic tool contains all procedures previously coded by their severity, avoiding the interference of user opinion.

Finally, the outcome postoperative in-hospital mortality, in spite of being a hard outcome, is basically affected by the prior clinical condition before surgery. In a recent cohort we observed that most postoperative deaths were considered inevitable (50.7%) in the postoperative period, as they were related to advanced illnesses and would occur regardless anaesthetic or surgical procedures [27]. Owing to these relatively short-life expectancies of the high-risk group patients, there has been some criticism on the use of perioperative risk prediction models when the system intends to inform patients about perioperative survival, as well as prioritize investments in the long-term survival of patients with relatively low rates of dying [28].

Thus, risk models should go beyond the mortality prediction, targeting perioperative complications, long-term rehabilitation and patient reported outcomes.

However, mortality risk prediction tools can boost the perioperative pathways modifications which may improve the value in health care. The perioperative care based on the risk-adapted approach, around patients need, may allow the rational use of resources, reducing the burden on low risk patient and improving the efficiency to the high-risk patient processes. This framework seems essential, considering that the perioperative care in some systems accounts for over half of hospital costs.

In conclusion, we have validated a consistent index for prediction of postoperative mortality after non-cardiac surgery. The four variables that compounded the original model were revisited and consistent analyses proved that the updated model had a high degree of accuracy. Yet, to make sense, the risk models development must be the foundation of multiprofessional risk-reduction strategies implementation during the entire perioperative patient's journey.

**Acknowledgments**

This study was supported by Project 2016-0229 from the Fundo de Incentivo à Pesquisa do Hospital de Clínicas de Porto Alegre (FIP-E-HCPA)

**Competing Interests**

This study receives no external funding. CSG, SMJC, LSMO, SCP and LCS declare no competing interests.

## References

1. Duceppe E, Parlow J, MacDonald P et al. Canadian Cardiovascular Society Guidelines on Perioperative Cardiac Risk Assessment and Management for Patients Who Undergo Noncardiac Surgery. *The Canadian Journal of Cardiology* 2017; **33**: 17–32.
2. Moonesinghe SR, Mythen MG, Das P, Rowan KM, Grocott MPW. Risk stratification tools for predicting morbidity and mortality in adult patients undergoing major surgery: qualitative systematic review. *Anesthesiology* 2013; **119**: 959–81.
3. Gualandro D, Yu P, Caramelli B et al. 3rd Guideline For Perioperative Cardiovascular Evaluation Of The Brazilian Society Of Cardiology. *Arquivos Brasileiros de Cardiologia* 2017; **109**.
4. Fleisher LA, Fleischmann KE, Auerbach AD et al. 2014 ACC/AHA guideline on perioperative cardiovascular evaluation and management of patients undergoing noncardiac surgery: executive summary: a report of the American College of Cardiology/American Heart Association Task Force on practice guidelines. Developed in collaboration with the American College of Surgeons, American Society of Anesthesiologists, American Society of Echocardiography, American Society of Nuclear Cardiology, Heart Rhythm Society, Society for Cardiovascular Angiography and Interventions, Society of Cardiovascular Anesthesiologists, and Society of Vascular Medicine Endorsed by the Society of Hospital Medicine. *Journal of Nuclear Cardiology: Official Publication of the American Society of Nuclear Cardiology* 2015; **22**: 162–215.
5. Stefani LC, Gutierrez CDS, Castro SM de J et al. Derivation and validation of a preoperative risk model for postoperative mortality (SAMPE model): An approach to care stratification. *PLOS ONE* 2017; **12**: e0187122.
6. Glance LG, Dick AW, Osler TM. Risk Prediction Tools: The Need for Greater Transparency. *Anesthesiology* 2018; **128**: 244–6.
7. Salisbury AC, Spertus JA. Realizing the Potential of Clinical Risk Prediction Models: Where Are We Now and What Needs to Change to Better Personalize Delivery of Care? *Circulation. Cardiovascular Quality and Outcomes* 2015; **8**: 332–4.
8. Gajdos C, Kile D, Hawn MT, Finlayson E, Henderson WG, Robinson TN.

- Advancing age and 30-day adverse outcomes after nonemergent general surgeries. *Journal of the American Geriatrics Society* 2013; **61**: 1608–14.
9. Yan Yan, Kimberly A. Reske, Victoria J. Fraser, Graham A. Colditz, Erik R. Dubberke. Using Appropriate Functional Forms for Continuous Variables and Improving Predictive Accuracy in Developing the Risk Model of Clostridium Difficile Infection. 2012; **10**: 37–49.
  10. Desquillet L, Mariotti F. Dose-response analyses using restricted cubic spline functions in public health research. *Statistics in Medicine* 2010; **29**: 1037–57.
  11. Gerdts TA, Cai T, Schumacher M. The performance of risk prediction models. *Biometrical Journal. Biometrische Zeitschrift* 2008; **50**: 457–79.
  12. Steyerberg EW, Vickers AJ, Cook NR et al. Assessing the performance of prediction models: a framework for traditional and novel measures. *Epidemiology (Cambridge, Mass.)* 2010; **21**: 128–38.
  13. Pencina MJ, D'Agostino RB, D'Agostino RB, Vasan RS. Evaluating the added predictive ability of a new marker: from area under the ROC curve to reclassification and beyond. *Statistics in Medicine* 2008; **27**: 157–72; discussion 207-212.
  14. Harrell F. *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*, 2nd edn. Springer International Publishing, 2015.
  15. Grunkemeier GL, Jin R. Net reclassification index: measuring the incremental value of adding a new risk factor to an existing risk model. *The Annals of Thoracic Surgery* 2015; **99**: 388–92.
  16. Feinstein AR, Wells CK, Walter SD. A comparison of multivariable mathematical methods for predicting survival--I. Introduction, rationale, and general strategy. *Journal of Clinical Epidemiology* 1990; **43**: 339–47.
  17. Protopapa KL, Simpson JC, Smith NCE, Moonesinghe SR. Development and validation of the Surgical Outcome Risk Tool (SORT). *The British Journal of Surgery* 2014; **101**: 1774–83.
  18. Glance LG, Lustik SJ, Hannan EL et al. The Surgical Mortality Probability Model: derivation and validation of a simple risk prediction rule for noncardiac

- surgery. *Annals of Surgery* 2012; **255**: 696–702.
19. Sutton R, Bann S, Brooks M, Sarin S. The Surgical Risk Scale as an improved tool for risk-adjusted analysis in comparative surgical audit. *The British Journal of Surgery* 2002; **89**: 763–8.
  20. Sepehri A, Beggs T, Hassan A et al. The impact of frailty on outcomes after cardiac surgery: a systematic review. *The Journal of Thoracic and Cardiovascular Surgery* 2014; **148**: 3110–7.
  21. Makary MA, Segev DL, Pronovost PJ et al. Frailty as a predictor of surgical outcomes in older patients. *Journal of the American College of Surgeons* 2010; **210**: 901–8.
  22. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics* 1988; **44**: 837–45.
  23. Cook NR. Statistical evaluation of prognostic versus diagnostic models: beyond the ROC curve. *Clinical Chemistry* 2008; **54**: 17–23.
  24. Wu Y-C, Lee W-C. Alternative performance measures for prediction models. *PloS One* 2014; **9**: e91249.
  25. Pearse RM, Moreno RP, Bauer P et al. Mortality after surgery in Europe: a 7 day cohort study. *Lancet (London, England)* 2012; **380**: 1059–65.
  26. ASA House of Delegates/Executive Committee. ASA Physical Status Classification System | American Society of Anesthesiologists (ASA). 2014. <https://www.asahq.org/standards-and-guidelines/asa-physical-status-classification-system> (accessed August 26, 2019).
  27. Stefani LC, Gamermann PW, Backof A et al. Perioperative mortality related to anesthesia within 48 h and up to 30 days following surgery: A retrospective cohort study of 11,562 anesthetic procedures. *Journal of Clinical Anesthesia* 2018; **49**: 79–86.
  28. Carlisle JB. Risk prediction models for major surgery: composing a new tune. *Anaesthesia* 2019; **74 Suppl 1**: 7–12.

**Table 1** Descriptive data for the total study population. Values are number (proportion).

	<b>Study population</b> <b>Total</b> <b>n = 16 618 (100%)</b>	<b>Deaths</b> <b>Total</b> <b>n = 465 (2.8%)</b>
<b>Gender</b>		
Men	7366 (44.3%)	238 (51.2%)
Women	9252 (55.6%)	227 (48.8%)
<b>Age; y</b>		
16 - 35	2734 (16.4%)	23 (4.9%)
36 - 55	5480 (32.9%)	2 (20.4%)
56 - 75	6985 (42%)	234 (50.3%)
> 75	1419 (8.5%)	113 (24.3%)
<b>ASA physical status</b>		
I	2779 (16.7%)	2 (0.4%)
II	9033 (54.3%)	42 (9%)
III	4206 (25.3%)	178 (38.3%)
IV	528 (3.1%)	186 (40%)
V	72 (0.4%)	57 (12.3%)
<b>Nature of procedure</b>		
Elective	13275 (79.8%)	132 (28.4%)
Urgent	3343 (20.1%)	333 (71.6%)
<b>Severity of procedure</b>		
Minor	6093 (36.6%)	79 (17%)
Intermediate	5792 (34.8%)	85 (18.3%)
Major	4733 (28.4%)	301 (64.7%)
<b>Surgical specialty</b>		
Urologic	2923 (17.5%)	37 (8%)
Digestive	2673 (16%)	123 (26.5%)
General	2489 (14.9%)	83 (17.8%)

Orthopedic	1554 (9.3%)	22 (4.7%)
Gynecologic	1458 (8.7%)	1 (0.2%)
Otorhinolaryngologic	1155 (6.9%)	6 (1.3%)
Cardiovascular	1008 (6%)	48 (10.3%)
Vascular	828 (4.9%)	51 (11%)
Neurosurgery	575 (3.4%)	53 (11.4%)
Coloproctology	515 (3.1%)	14 (3%)
Mastology	500 (3%)	0 (0%)
Thoracic	457 (2.7%)	27 (5.8%)
Plastic	375 (2.2%)	0 (0%)
Oral and Maxillo	97 (0.5%)	0 (0%)
Pediatric	11 (0.1%)	0 (0%)

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ASA, American Society of Anesthesiologists.

**Table 2** Coefficients for the original SAMPE model. The outcome is postoperative in-hospital mortality. Variables included in the model with respective odds ratios and confidence intervals (n = 16 618).

Variable	Odds ratio Original SAMPE	95% Confidence Interval	p	
Age	1.029	1.021-1.03	< 0.001	
ASA class	6.68	5.67-7.87	< 0.0001	
Intermediate vs Minor	0.77	0.54-1.08	0.131	
Major vs Minor	1.46	1.10-1.94	0.008	
Status (non-elective vs elective)	4.29	3.39-5.42	< 0.0001	H o

smer Lameshow Goodness-of-Fit Test - Chi-Square: 16.69; p = 0.0334.  
ASA, American Society of Anesthesiologists.

**Table 3** Variables included in the new model (SAMPE II) with respective odds ratios and confidence intervals after variables adjustments (n = 16 618).

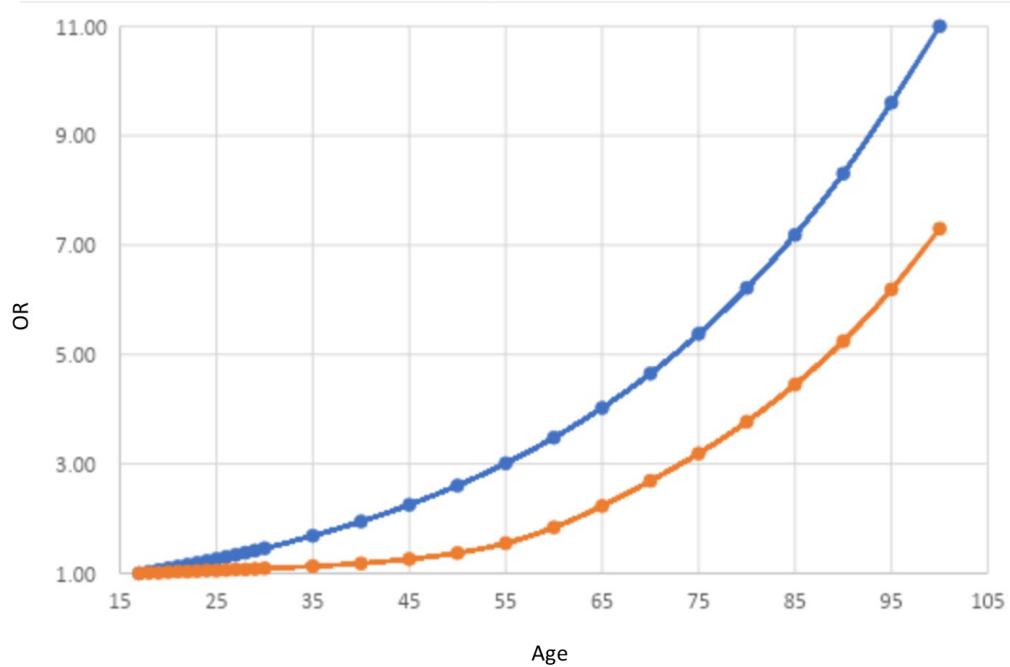
Variable	Odds ratio	95% confidence interval	p
Age, years (splines) 17 (Ref)	1.00	1.00	
30	1.09	0.55-2.16	NS
50	1.38	0.55-3.45	NS
60	1.84	0.80-4.26	NS
70	2.70	1.11-6.52	< 0.01
80	3.78	1.58-9.01	< 0.01
90	5.27	2.12-13.11	< 0.01
ASA class	6.66	5.65-7.84	< 0.0001
Major vs non-Major	1.69	1.35-2.13	< 0.0001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

SAMPE, Anaesthesia and Perioperative Service; ASA, American Society of Anesthesiologists.

**Table 4** Prognostic capability of SAMPE II model in predicting postoperative death according to each risk class.

SAMPE risk class (predicted mortality)	Number of patients	Deaths (%)	Hazard ratio (95% CI)	p value
Class I: < 2%	12810	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

SAMPE, Anaesthesia and Perioperative Service; CI, Confidence Interval.



**Figure 1** The curve shows the Odds of probability of in-hospital death up to 30-days after surgery as a function of age using restricted cubic splines (orange) vs age in a linear manner (blue).

## Supplementary Material

**Table S1** Comparison of the Clinical performance of SAMPE II vs original SAMPE model.

	<b>Original SAMPE model n= 16 618</b>	<b>SAMPE II n= 16 618</b>		
<b>SAMPE Risk class (Predicted mortality)</b>	<b>Total</b>	<b>Deaths (%)</b>	<b>Total</b>	<b>Deaths (%)</b>
Class I: < 2%	12661	51 (0.4)	12810	53 (0.41)
Class II: between 2 and 5%	2248	71 (3.16)	2035	63 (3.10)
Class III: between 5 and 10%	653	51 (7.81)	751	53 (7.06)
Class IV: > 10%	1056	292 (27.65)	1022	296 (28.96)
<b>Performance measures</b>				
Discrimination - AUC - C Statistic	0.927 – CI 0.91-0.03		0.926 (CI 0.91-0.93)	
Calibration - Hosmer Lameshow (chi-square)	16.69 (p= 0.0334)		9.26 (p= 0.41)	
Brier score	0.034755		0.019	

**Table S2** Reclassification of risk (30 day probability of death) for those who did and did not experience primary outcome in the original SAMPE model compared with the SAMPE II model.

	<b>Outcome present</b>				
	<b>SAMPE II model risk class</b>				<b>% Reclassification</b>
<b>Original SAMPE model risk class</b>	<b>0-2%</b>	<b>2-5 %</b>	<b>5-10%</b>	<b>&gt;10%</b>	
0-2%	49	2	0	0	4
2-5 %	4	60	7	0	15
5-10%	0	1	42	8	18
>10%	0	0	4	288	1
	<b>Outcome absent</b>				
0-2%	12554	56	0	0	0
2-5 %	203	1887	87	0	13
5-10%	0	29	541	32	10
>10%	0	0	70	694	9

# TRIPOD Checklist: Prediction Model Development and Validation

Section/Topic	Item		Checklist Item	Page
<b>Title and abstract</b>				
Title	1	D;V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	146
Abstract	2	D;V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	148
<b>Introduction</b>				
Background and objectives	3a	D;V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	149
	3b	D;V	Specify the objectives, including whether the study describes the development or validation of the model or both.	150
<b>Methods</b>				
Source of data	4a	D;V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	150
	4b	D;V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	150
Participants	5a	D;V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	150
	5b	D;V	Describe eligibility criteria for participants.	150
	5c	D;V	Give details of treatments received, if relevant.	150
Outcome	6a	D;V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	150
	6b	D;V	Report any actions to blind assessment of the outcome to be predicted.	NA
Predictors	7a	D;V	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	150
	7b	D;V	Report any actions to blind assessment of predictors for the outcome and other predictors.	150-152
Sample size	8	D;V	Explain how the study size was arrived at.	NA
Missing data	9	D;V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	NA
Statistical analysis methods	10a	D	Describe how predictors were handled in the analyses.	151-152
	10b	D	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.	151-153
	10c	V	For validation, describe how the predictions were calculated.	153-157
	10d	D;V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	151-153
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.	151-153
Risk groups	11	D;V	Provide details on how risk groups were created, if done.	171
Development vs. validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.	151-154
<b>Results</b>				
Participants	13a	D;V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	150
	13b	D;V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	167
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).	NA
Model development	14a	D	Specify the number of participants and outcome events in each analysis.	154
	14b	D	If done, report the unadjusted association between each candidate predictor and outcome.	NA
Model specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).	169-172
	15b	D	Explain how to use the prediction model.	NA
Model performance	16	D;V	Report performance measures (with CIs) for the prediction model.	169; 172
Model-updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).	155-157
<b>Discussion</b>				
Limitations	18	D;V	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).	161-162
Interpretation	19a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.	157-162
	19b	D;V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.	157-162
Implications	20	D;V	Discuss the potential clinical use of the model and implications for future research.	162
<b>Other information</b>				
Supplementary information	21	D;V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	173-174
Funding	22	D;V	Give the source of funding and the role of the funders for the present study.	163

\*Items relevant only to the development of a prediction model are denoted by D, items relating solely to a validation of a prediction model are denoted by V, and items relating to both are denoted D;V. We recommend using the TRIPOD Checklist in conjunction with the TRIPOD Explanation and Elaboration document.

## 8 CONSIDERAÇÕES FINAIS

Com o aumento da expectativa de vida e os crescentes avanços no campo da medicina, cada vez mais iremos nos deparar com pacientes complexos, candidatos a diferentes tipos de cirurgia. A identificação objetiva do risco auxilia não apenas no direcionamento das intervenções clínicas práticas, mas no compartilhamento de decisões, na alocação de recursos e no planejamento de estratégias custo-efetivas no campo da saúde. Nesse contexto, modelos e escores e risco podem ser ferramentas auxiliares no gerenciamento do cuidado perioperatório.

O produto desta Tese foi uma ferramenta de estratificação de risco pré-operatório, desenvolvida a partir de dados de um hospital brasileiro do Sistema Único de Saúde. O modelo SAMPE é o primeiro modelo de risco nacional de mortalidade pós-operatória, que utiliza poucas variáveis, podendo ser aplicado à beira do leito em diferentes tipos de cirurgia. O desenvolvimento de uma ferramenta *web based* de baixo custo e acessível, fez com que o modelo SAMPE fosse amplamente aceito e utilizado na prática clínica pelos anestesiologistas do Hospital de Clínicas de Porto Alegre. A introdução da estratificação de risco como parte da rotina assistencial, tornou evidente a necessidade de planejarmos o cuidado perioperatório adaptado ao risco do paciente. A identificação objetiva dos pacientes de alto risco permitiu a idealização de linhas de cuidado compatíveis, facilitando a comunicação entre as equipes e os processos de transferência de cuidados.

Nesse cenário, o Modelo SAMPE apresenta-se como uma alternativa promissora em termos de estratificação de risco cirúrgico no Brasil. A criação desse modelo de estratificação de risco, o qual é simples, acessível, acurado e validado em diferentes tipos de cirurgia, seguiu os passos recomendados por *guidelines* internacionais conforme exposto ao longo desta tese.

## 9 PERPECTIVAS FUTURAS

O gerenciamento pós-operatório adaptado ao risco é uma das medidas propostas para enfrentar o desafio de melhorar a experiência do paciente, a saúde da população como um todo e a otimização dos recursos em saúde. Ações voltadas para a melhoria dos processos de transferência, decisões compartilhadas em relação à alocação pós-operatória e planejamento de alta individualizados, podem auxiliar na diminuição da morbimortalidade pós-operatória. A população cirúrgica, é responsável por grande parte do consumo dos recursos destinados a saúde. O gasto é ainda mais substancial quando se considera a grande probabilidade que esses pacientes tem de complicações no pós-operatório. Portanto, é necessário mapear-se a mortalidade dos pacientes cirúrgicos no Brasil, nas diferentes regiões, instituições e sistemas de saúde. Um modelo de risco robusto auxiliará nessas comparações e no desenho de políticas voltadas à melhoria do acesso ao tratamento cirúrgico.

Tendo esses desafios em mente, o grupo de pesquisa em medicina perioperatória do SAMPE está trabalhando em projetos que visam melhorar os desfechos dos pacientes cirúrgicos de alto risco.

- ◆ Validação externa do Modelo SAMPE II utilizando coortes provenientes de diferentes hospitais do Brasil;
- ◆ Implantação e análise de impacto do projeto “Cuidados Estendidos ao Paciente Cirúrgico de Alto Risco” (CEPAR), que envolve um pacote de cuidados diferenciado aos pacientes de alto risco nas primeiras 48 horas pós-operatórias;
- ◆ Análise de custo dos processos envolvidos no pacote de cuidados do CEPAR.