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ORIGINAL ARTICLE

Clinical decision support system for risk stratification of unplanned ICU readmission: from model development to transition-of-care planning

Suporte à decisão clínica para estratificação de risco de readmissão não planejada em UTI: do modelo à transição de cuidado

Soporte a la decisión clínica para estratificación de riesgo de reingreso no planificado en UCI: del modelo a la transición asistencial

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ABSTRACT

Context: Unplanned ICU readmission is a frequent adverse event and a difficult outcome to predict. **Objective:** To develop and validate a predictive model for ICU readmission within seven days, operationalized as a mobile-first screening tool. **Methods:** Multicenter retrospective study (five hospitals; 15,461 ICU admissions, 2023–2024). Of 10,169 eligible patients (799 readmissions, 7.9%), 1,546 were excluded for missing predictor data, mainly Clinical Frailty Scale. Complete-case development and internal validation included 8,623 patients (678 readmissions, 7.9%), analyzed by binary logistic regression with bootstrap validation (1,000 replications) and multiple imputation. The CDSS was implemented in R/Shiny and evaluated by Think Aloud testing with five physicians. **Results:** Admission source was the strongest predictor (ward: OR 1.71; 95% CI 1.29–2.26; hemodynamics unit: 1.50; emergency department: 1.40), followed by SOFA (OR 1.08 per point; 1.05–1.10). Discrimination was limited (AUC 0.616; 95% CI 0.594–0.638; optimism-corrected 0.607), with adequate calibration (mean absolute error 0.004; Brier score 0.0717). Readmission rates were 4.3%, 7.7% and 11.4% in the low, intermediate and high strata, with positive net benefit between 5% and 15% and high usability (SUS 99.5). **Conclusion:** The CDSS combines interpretable statistics, TRIPOD-compliant validation and an EHR-independent architecture, supporting its use as a complementary screening instrument dependent on external validation.

Keywords: Patient Readmission; Decision Support Systems, Clinical; Logistic Models.

RESUMO

Contexto: A readmissão não planejada em UTI é evento adverso frequente e de predição difícil. **Objetivo:** Desenvolver e validar modelo preditivo de readmissão em até sete dias, operacionalizado como ferramenta de triagem mobile-first. **Método:** Estudo retrospectivo multicêntrico (cinco hospitais; 15.461 internamentos, 2023–2024). Dos 10.169 elegíveis (799 readmissões; 7,9%), 1.546 foram excluídos por dados ausentes, sobretudo na Escala de Fragilidade Clínica; 8.623 casos completos (678 readmissões; 7,9%) foram analisados por regressão logística com validação por bootstrap (1.000 repetições) e imputações múltiplas. O SSDC foi implementado em R/Shiny e avaliado por Think Aloud com cinco médicos. **Resultados:** A origem da admissão foi o principal preditor (enfermaria: OR 1,71; IC95% 1,29–2,26; unidade hemodinâmica: 1,50; emergência: 1,40), seguida do SOFA (OR 1,08/ponto; 1,05–1,10). A discriminação foi limitada (AUC 0,616; IC95% 0,594–0,638; corrigida 0,607) com calibração adequada (erro absoluto médio 0,004; Brier 0,0717). A readmissão observada foi 4,3%, 7,7% e 11,4% nos estratos baixo, intermediário e alto, com benefício líquido positivo entre 5% e 15% e usabilidade elevada (SUS 99,5). **Conclusão:** O SSDC combina estatística interpretável, validação TRIPOD e arquitetura independente do prontuário, sustentando seu uso como instrumento complementar de triagem, dependente de validação externa.

Descritores: Readmissão do Paciente; Sistemas de Apoio a Decisões Clínicas; Modelos Logísticos.

RESUMEN

Contexto: El reingreso no planificado en UCI es un evento adverso frecuente y de predicción difícil. **Objetivo:** Desarrollar y validar un modelo predictivo de reingreso en siete días, operacionalizado como herramienta de cribado mobile-first. **Método:** Estudio retrospectivo multicéntrico (cinco hospitales; 15.461 ingresos, 2023–2024). De los 10.169 elegibles (799 reingresos; 7,9%), 1.546 fueron excluidos por datos ausentes, sobre todo en la Escala de Fragilidad Clínica; 8.623 casos completos (678 reingresos; 7,9%) se analizaron mediante regresión logística con validación por bootstrap (1.000 repeticiones) e imputaciones múltiples. El SSDC se implementó en R/Shiny y se evaluó mediante prueba Think Aloud con cinco médicos. **Resultados:** El origen del ingreso fue el principal predictor (hospitalización: OR 1,71; IC95% 1,29–2,26; unidad hemodinámica: 1,50; urgencias: 1,40), seguido del SOFA (OR 1,08/punto; 1,05–1,10). La discriminación fue limitada (AUC 0,616; IC95% 0,594–0,638; corregida 0,607) con calibración adecuada (error absoluto medio 0,004; Brier 0,0717). El reingreso observado fue 4,3%, 7,7% y 11,4% en los estratos bajo, intermedio y alto, con beneficio neto positivo entre 5% y 15% y usabilidad elevada (SUS 99,5). **Conclusión:** El SSDC combina estadística interpretable, validación TRIPOD y arquitectura independiente de la historia clínica, sustentando su uso como cribado complementario, dependiente de validación externa.

Descriptores: Readmisión del Paciente; Sistemas de Apoyo a Decisiones Clínicas; Modelos Logísticos.

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1 INTRODUCTION

Unplanned ICU readmission is a relevant adverse event associated with increased morbidity, mortality, prolonged hospital length of stay and higher costs [1,2]. Reported incidences range between 1.5% and 13.4% among patients discharged from the ICU, with variability explained by differences in study population, operational definition and time window [3]. The multifactorial nature of the outcome makes its prediction a clinically complex problem in which no single variable exhibits dominant discriminatory power [4–6]. Prediction models generally demonstrate modest to moderate discrimination [5,7,8], and systematic reviews highlight the lack of accurate, transportable models for direct bedside application [4, 9]. This gap stems from recognized factors: the interpretive opacity of complex algorithms undermines clinician trust and auditability [10,11]; reliance on an integrated Electronic Health Record (EHR) is restrictive in systems with heterogeneous infrastructure, as observed in Brazilian hospitals [12]; and existing systems often mismatch the rapid, multiprofessional pace of ICU decision-making [13].

Clinical Decision Support Systems (CDSS) integrate patient data and predictive algorithms to support care at the point of delivery [14]. Their effectiveness is not determined by accuracy alone: actionable recommendations, workflow integration and low interaction burden are most consistently associated with benefit [13], while tools requiring extensive data entry tend to be abandoned irrespective of statistical performance [10]. Logistic regression suits this purpose, as interpretable coefficients allow clinicians to inspect each variable's contribution to estimated risk [15]. Discrimination and calibration are distinct properties frequently conflated in reporting. In low-prevalence, multifactorial outcomes discrimination is typically modest, and usefulness depends more on calibration and interpretable risk strata than on a high area under the curve [4,9,15]. This underpins risk stratification, in which patients are grouped by observed event rates to guide the intensity of subsequent care rather than to support individual diagnostic decisions [4,9]. Where discrimination is naturally limited, the CDSS should serve as a screening instrument based on risk strata and calibration [4,9,16, 17], supporting structured transition planning rather than replacing clinical judgment. In Brazilian ICUs, case-mix and severity differ substantially between public and private institutions [18], which constrains the transportability of models developed in single-center or fully integrated systems. Transition-of-care programs with early follow-up and defined escalation criteria are associated with lower readmission and mortality after ICU discharge [19,20]. This study therefore aims to develop and internally validate a prediction model for unplanned ICU readmission within seven days and to operationalize it as an EHR-independent, web-based CDSS designed for bedside use by intensive care physicians.

2 METHODS

2.1 Design and setting

A multicenter retrospective cohort study of clinical prediction model development and internal validation was conducted, following the TRIPOD recommendations [16]. The cohort comprised patients admitted to the ICUs of five hospitals, encompassing different strata of the supplementary and philanthropic health system and varying levels of complexity, with surgical, general and polyvalent care profiles.

2.2 Participants, outcome and sample size

Eligible patients were adults admitted to the participating ICUs between January 2023 and December 2024 (15,461 admissions), excluding records with missing essential variables, death during the first admission, transfer to another hospital or continued admission at data extraction. Complete-case analysis was the primary strategy: of 10,169 eligible adults (799 unplanned readmissions, 7.9%), 1,546 (15.2%) were excluded for missing predictor data, predominantly missing Clinical Frailty Scale (CFS) (n=1,545), leaving 8,623 complete cases (678 readmissions, 7.9%) for modeling and bootstrap validation. The outcome was unplanned ICU readmission within seven days of discharge during the same hospitalization, analyzed dichotomously and stratified as early (≤24 h) or late (24 h–7 d); planned returns were excluded. Minimum sample size, calculated according to Riley et al. [17] for a prevalence of 7.9%, an expected AUC of 0.75 [9] and maximum shrinkage of 0.9, was 957 and 1,094 patients; the obtained sample was approximately ten times these minimums (114 and 100 events per variable). Included and excluded patients were compared (absolute SMD <0.10 considered small). In a sensitivity analysis, 20 multiple imputations of missing CFS values were performed with an ordinal logistic model conditional on observed predictors and outcome, with estimates combined using Rubin's rules.

2.3 Data collection and candidate predictors

Data were extracted anonymously from the electronic database of the participating centers, managed on REDCap® and fed daily by intensive care physicians. Candidate predictors were prespecified on clinical grounds and on the literature [1,4–6], in three blocks. Epidemiological: age, sex, chronic comorbidities and payer source (Brazilian Unified Health System - SUS versus other). Primary admission: Clinical Frailty Scale in the first 24 hours as continuous [21]; APACHE II [22]; admission SOFA [23]; type of admission (medical, elective surgical, urgent surgical); admission source (emergency department, ward, operating room);

advanced life support (mechanical ventilation, vasoactive drugs, renal replacement therapy, tracheostomy); and complications (bacterial infection, acute kidney injury). Discharge: ICU length of stay, functional capacity on a four-level ordinal scale developed for the study, and discharge SOFA.

2.4 Statistical analysis

Categorical variables were described as frequencies and percentages, and quantitative variables as mean and standard deviation or median and interquartile range, as appropriate. Bivariate comparisons used Pearson's chi-square or Fisher's exact test, Student's t-test or Mann-Whitney U-test, with ANOVA/Bonferroni or Kruskal-Wallis for multiple comparisons. Predictive modeling used binary logistic regression with predictors prespecified on clinical grounds, fitted by the Enter method without stepwise selection or regularization [15,16]. APACHE II was excluded for overlap with age and admission SOFA [23,24], the latter retained for its dynamic nature and parsimony [24]; an alternative model added discharge SOFA and ICU length of stay. Effects were expressed as odds ratios with 95% CI (Wald test, α=5%). Performance was assessed by discrimination (AUC with 95% CI; Tjur coefficient of discrimination), overall fit (AIC, interpreted comparatively between models), calibration (deciles plot; calibration mean absolute error) and overall performance (Brier score). Internal validation used bootstrap resampling with 1,000 replications, generating optimism-corrected AUC and Brier estimates [15]. Missing predictor data were handled by complete-case analysis, with included and excluded patients compared by standardized mean differences (<0.10 considered small) and, in a sensitivity analysis, by 20 multiple imputations of missing CFS values using an ordinal logistic imputation model, with coefficients combined by Rubin's rules and results interpreted descriptively. Predicted probabilities were categorized post hoc into low (<5%), intermediate (5% to <10%) and high (≥10%) strata [15]; these cut-offs were not derived from data-driven optimization and are presented for risk communication only, not as validated decision thresholds. Decision curve analysis compared the net benefit of the model with treat-all and treat-none strategies across thresholds from 1% to 25%. Analyses were performed in R version 4.0.

2.5 CDSS implementation

To facilitate clinical translation, the predictive model was operationalized as an interactive clinical decision support system (CDSS) developed using the R/Shiny framework [25]. The use of R in both the modeling and implementation phases ensured that the equations executed by the CDSS corresponded exactly to those estimated during development. The system's architecture was guided by three core design principles: (1) a mobile-first concept, optimized for smartphones and tablets to seamlessly integrate into bedside clinical rounds; (2) complete independence from the Electronic Health Record (EHR), requiring no APIs, federated authentication, or institutional data buses, with risk queries performed autonomously via manual entry of predictor values; and (3) strict compliance with the Brazilian General Data Protection Law (LGPD), achieved by hosting the application on a secure cloud server via HTTPS with no persistent storage of user data, thereby adhering to the principles of data minimization and necessity. Computational consistency was assessed in 100 clinical records selected across the low-, intermediate- and high-risk strata (34, 33 and 33 records, respectively). Predictions from the original fitted model were compared with probabilities obtained from the full-precision logistic equation and from a reproduction of the application's input-processing and prediction workflow. We assessed maximum and mean absolute differences, agreement within a prespecified numerical tolerance of 10^{-10}, and agreement in risk-stratum classification.

2.6 Usability evaluation

Usability was evaluated in two phases [26]: a heuristic inspection [27], then a think-aloud pilot test with a convenience sample of five intensive care physicians [28]. Participants performed three tasks on fictitious cases (data entry, risk interpretation and appraisal of recommendations) while the observer recorded completion, time and errors. They then completed the System Usability Scale (SUSc) [29], interpreted against normative benchmarks (mean ≈ 68; > 80.3 = grade A) [30], and three 5-point items on risk clarity, decision speed and independence from the EHR. Analysis was descriptive.

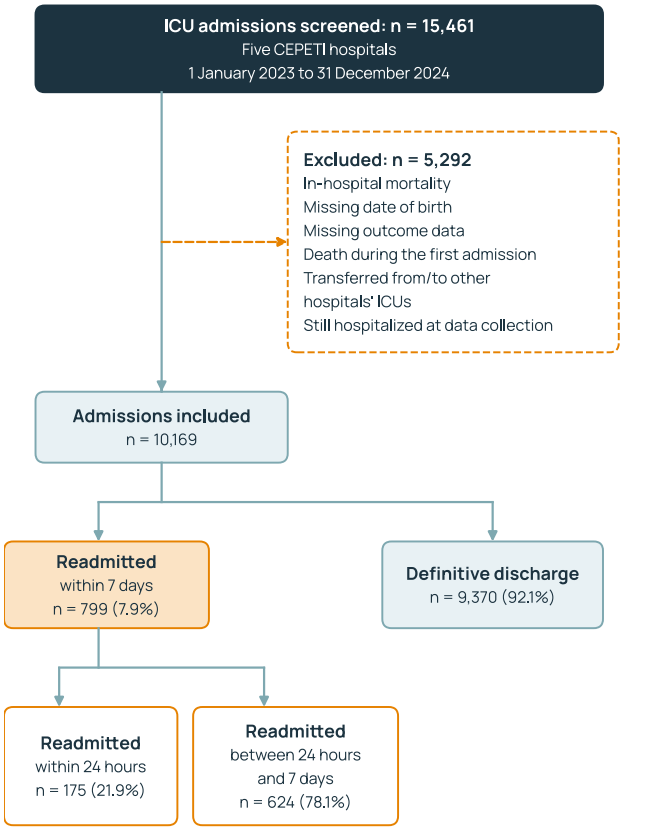
2.7 Ethics

The project was approved by the Research Ethics Committee of the Pontifícia Universidade Católica do Paraná (CAAE 85995125.0.0000.0020; opinions 7.351.395 and 8.411.760, the latter for the amendment that introduced the usability test). Waiver of informed consent was granted for the retrospective cohort; usability pilot participation was conditional on informed consent. All procedures complied with Brazilian Federal Law 14,874/2024, National Health Council Resolutions 466/2012 and 510/2016, the Declaration of Helsinki and the LGPD.

3 RESULTS

The complete-case analysis and the bootstrap analyses were both performed on the 8,623 patients with complete predictor data, corresponding to 84.8% of the 10,169 eligible patients. Of the 15,461 ICU admissions screened, 10,169 adult patients met the eligibility criteria (analytic cohort; 799 unplanned readmissions,

Figure 1. Flowchart of the patient selection process, including exclusion criteria and the final cohort for model development and validation.



Source: Prepared by the authors (2026).

7.9%) between January 2023 and December 2024 (Figure 1). The remaining 1,546 eligible records (15.2%) had missing predictor information (1,545 missing CFS values and one missing admission SOFA value). Complete-case model development and internal validation therefore included 8,623 patients (678 unplanned readmissions, 7.9%), and this sample was used in all multivariable modeling, bootstrap validation and decision curve analysis.

Readmitted patients were older (68 ± 16 vs. 64 ± 17 years), more often male (53% vs. 48%), had a higher burden of comorbidities (92% vs. 89%) and were more frequently covered by the public health system (45% vs. 40%). They also had higher CFS (median 4 [IQR 3–5] vs. 3 [IQR 3–4]), APACHE II (median 12 [IQR 8–19] vs. 10 [IQR 6–15]) and admission SOFA (median 2 [IQR 1–5] vs. 1 [IQR 0–4]), and more often received vasoactive drugs, mechanical ventilation, renal replacement therapy and tracheostomy. Readmitted patients came less frequently from the operating room (26% vs. 35%) and more often from the emergency department (53% vs. 48%), had longer ICU stay (3 [IQR 1–5] vs. 2 [IQR 1–4] days) and higher discharge SOFA (all $p<0.05$) (Table 1).

Of the 799 readmitted patients, 175 (21.9%) returned within 24 hours and 624 (78.1%) between 24 hours and 7 days. Clinical and epidemiological profiles were homogeneous between subgroups for most variables, with distinction only for acute kidney injury, approximately three times more frequent in early readmissions (3.4% vs. 1.1%; $p=0.044$), supporting the premise that vulnerability is established early in the critical illness trajectory. To assess selection bias from missing predictor data, the development sample (n=8,623) was compared with the 1,546 excluded patients (Table 2). Groups were similar in age, admission source, admission type and unplanned readmission; significant but small differences were found for sex (51% vs. 48%; $p=0.040$; SMD=0.057) and payer source (37% vs. 41%; $p=0.003$; SMD=0.082). All characteristics had absolute SMDs <0.10, and readmission rates were nearly identical (7.8% vs. 7.9%; $p>0.90$; SMD=0.001).

Table 3 presents the independent predictors of unplanned 7-day readmission, together with the estimates from the sensitivity analysis with 20 imputations of missing CFS values. Admission source carried the highest risk: ward (adjusted OR 1.71; 95% CI 1.29–2.26), hemodynamics unit (OR 1.50; 95% CI 1.09–2.05) and emergency department (OR 1.40; 95% CI 1.15–1.71; $p\leq0.001$ for all). Admission SOFA (OR 1.08 per point; 95% CI 1.05–1.10), male sex (OR 1.22; 95% CI 1.04–1.44) and age (OR 1.01 per year; 95% CI 1.00–1.01) were also independent predictors. CFS (OR 1.05; 95% CI 0.99–1.11), admission type and payer source were retained in the model without reaching significance. In the imputed analysis, which increased the sample to 10,169 patients and 799 events, estimates were broadly unchanged (SOFA OR 1.074; CFS OR 1.06; ward origin OR 1.68). The AIC of the main model was 4,664.6.

The mathematical coefficients, standard errors, and intercept of the final logistic regression model are available in Table 4. The final equation of the logistic regression model was expressed on a logit scale. The individual probability of unplanned readmission was calculated by: $p = 1/(1 + e^{-LP})$, where LP corresponds to the linear predictor: $LP = -3.600 + 0.00705 \times age + 0.202 \times male\ sex + 0.0485 \times frailty + 0.0734 \times SOFA + 0.536 \times ward\ origin + 0.406 \times hemodynamic\ unit + 0.336 \times emergency\ department\ origin - 0.275 \times elective\ surgical\ admission - 0.0667 \times clinical\ admission + 0.119 \times SUS$ (Brazilian Unified Health System). The reference categories were: female sex, operating room origin, emergency surgical admission, and non-SUS payer.

Figure 2 presents the ROC curves for the two predictive models evaluated. The main model had an apparent AUC of 0.6159 (95% CI 0.5943–0.6375), with bootstrap optimism of 0.0090 and an optimism-corrected AUC of 0.6069 (95% CI 0.5870–0.6272); its Tjur coefficient was 0.0131. The alternative model had an apparent AUC of 0.6216 (95% CI 0.5997–0.6436). Discrimination was therefore limited in both models, and the difference between them was small, with widely overlapping confidence intervals and extensive overlap of the

Table 1. Baseline characteristics of patients with and without unplanned ICU readmission within 7 days.

Variable	Readmitted (n=799)	Definitive Discharge (n=9,370)	p value
Age, years, mean (SD)	68 ± 16	64 ± 17	<0.001§
Male sex, n (%)	420 (53%)	4,539 (48%)	0.025#
At least one comorbidity, n (%)	732 (92%)	8,302 (89%)	0.009#
SUS as payer source, n (%)	359 (45%)	3,775 (40%)	0.010#
Clinical Frailty Scale, median (IQR)	4.00 (3.00, 5.00)	3.00 (3.00, 4.00)	<0.001*
Admission source, n (%)			<0.001#
Operating room	205 (26%)	3,296 (35%)	
Ward	99 (12%)	849 (9.1%)	
Hemodynamics unit	69 (8.6%)	732 (7.8%)	
Emergency department	426 (53%)	4,493 (48%)	
Type of admission, n (%)			<0.001#
Emergency surgical	72 (9%)	780 (8.3%)	
Elective surgical	211 (26%)	3,080 (33%)	
Medical	516 (65%)	5,507 (59%)	
APACHE II (first 24 h), median (IQR)	12 (8, 19)	10 (6, 15)	<0.001*
Admission SOFA, median (IQR)	2.00 (1.00, 5.00)	1.00 (0.00, 4.00)	<0.001*
Mechanical ventilation during ICU stay, n (%)	132 (17%)	1,182 (13%)	0.002#
Vasoactive drugs during ICU stay, n (%)	275 (34%)	2,755 (29%)	0.003#
Renal replacement therapy during ICU stay, n (%)	29 (3.6%)	147 (1.6%)	<0.001#
Tracheostomy during ICU stay, n (%)	21 (2.6%)	98 (1.0%)	<0.001#
Bacterial infection during ICU stay, n (%)	162 (20%)	1,211 (13%)	<0.001#
Acute kidney injury, n (%)	13 (1.6%)	142 (1.5%)	0.8#
Functional capacity at discharge, n (%)			0.002#
Independent in all activities	271 (37%)	4,015 (43%)	
Dependent in all activities	61 (8.3%)	563 (6.0%)	
Requiring assistance in basic activities	123 (17%)	1,346 (14%)	
Requiring assistance in complex activities	283 (38%)	3,441 (37%)	
Length of stay, days, median (IQR)	3.00 (1.00, 5.00)	2.00 (1.00, 4.00)	<0.001*
Length of stay band, days, n (%)			<0.001#
1–2	370 (46%)	5,485 (59%)	
3–7	315 (39%)	3,202 (34%)	
>7	114 (14%)	683 (7.3%)	
Discharge SOFA, median (IQR)	1.00 (0, 3.00)	1.00 (0, 2.00)	<0.001*

Analytic cohort (n=10,169). Abbreviations: APACHE II: Acute Physiology and Chronic Health Evaluation; SOFA: Sequential Organ Failure Assessment; RRT: Renal Replacement Therapy; ICU: Intensive Care Unit. The results for categorical variables are described by absolute frequency (percentage), while the results for quantitative variables are described by mean ± standard deviation; median (first quartile - third quartile). § Student's t-test significance * Mann-Whitney U test significance # Pearson's x^2 test. - Chi-square test due to low expected frequencies. Functional capacity at ICU discharge was rated by the attending intensivist on a four-level ordinal scale developed for this study: (1) independent in all activities: performs all basic and instrumental activities of daily living without assistance; (2) requires assistance with complex activities: independent in basic self-care but needs help with instrumental activities (e.g., medication management, mobility outside the bed); (3) requires assistance with basic activities: needs help with basic activities of daily living (e.g., bathing, dressing, transferring); (4) dependent in all activities: requires full assistance for all basic activities.

Source: Prepared by the authors (2026).

curves across most of the probability spectrum.

Figure 3 shows the calibration plot of the main model. The optimism-corrected curve followed the ideal diagonal across the 0.05–0.20 range of predicted probabilities, without a systematic pattern of under- or over-estimation, and the calibration mean absolute error between predicted and observed rates was 0.004. The optimism-corrected Brier score was 0.0717, marginally lower than the value expected from a null model assigning the baseline readmission rate (7.9%) to every patient (0.0728).

Decision curve analysis was used to evaluate the clinical utility of the main model across a threshold range from 1% to 25%, with the clinically relevant thresholds summarized in Figure 4. The model showed a positive net benefit across the clinically relevant threshold range. At the 5.0%, 7.5%, 10.0%, 12.5% and 15.0% thresholds, the net benefits of the model were 0.0314, 0.0159, 0.00327, 0.00227 and 0.0017, respectively. At the 5.0% threshold, the net benefit of the model was 0.0314 against 0.0301 for the treat-all strategy, a difference of 0.0013. At the 7.5% threshold, the net benefit of treat-all remained positive (0.0039) but was already lower than that of the model (0.0159); from the 10.0% threshold onwards, treat-all became unfavorable (−0.0237 and −0.0530 at 10.0% and 12.5%, respectively), whereas the model retained a positive net benefit at all evaluated thresholds. The treat-none strategy had a net

Table 2. Comparison between patients included and excluded due to missing data.

Characteristic	Excluded due to missing data (N=1,546)	Included (N=8,623)	p-value	SMD
Age (years)	65 ± 17; 67 (54–77)	65 ± 17; 67 (53–77)	0.5	0.015
Sex (male)	791 (51%)	4,168 (48%)	0.040	0.057
Admission source			0.2	0.059
Operating room	529 (34%)	2,972 (34%)		
Ward	153 (9.9%)	795 (9.2%)		
Hemodynamics unit	140 (9.1%)	661 (7.7%)		
Emergency department	724 (47%)	4,195 (49%)		
Type of admission			>0.9	0.007
Emergency surgical	132 (8.5%)	720 (8.3%)		
Elective surgical	498 (32%)	2,796 (32%)		
Medical	916 (59%)	5,107 (59%)		
SUS as payer source	576 (37%)	3,558 (41%)	0.003	0.082
Unplanned readmission	121 (7.8%)	678 (7.9%)	>0.9	0.001

SMD: standardized mean difference. Absolute SMD values < 0.10 indicate small differences.

Source: Prepared by the authors (2026).

Table 3. Predictors of unplanned ICU readmission within seven days, complete-case and multiple-imputation estimates.

Predictor	Complete-case - Adjusted OR	Complete-case – 95% CI	Complete-case – p value	20 multiple imputations combined OR	20 multiple imputations -95% CI
Age (years)	1.01	1.00–1.01	0.009	1.01	(1.00–1.01)
Sex	1.22	1.04–1.44	0.014	1.17	(1.01–1.35)
Clinical Frailty Scale	1.05	0.99–1.11	0.10	1.06	(0.98–1.12)
Admission SOFA	1.08	1.05–1.10	<0.001	1.07	(1.05–1.10)
Admission source					
Operating room (reference)	-	-	-	-	-
Ward	1.71	1.29–2.26	<0.001	1.68	(1.23–2.18)
Hemodynamics unit	1.50	1.09–2.05	0.012	1.50	(1.12–2.00)
Emergency department	1.40	1.15–1.71	0.001	1.44	(1.20–1.74)
Type of admission					
Emergency surgical (reference)	-	-	-	-	-
Elective surgical	0.76	0.56–1.04	0.076	0.87	(0.65–1.15)
Medical	0.94	0.71–1.25	0.6	0.95	(0,73–1.24)
Payer source	1.13	0.95–1.33	0.2	1.13	(0.97–1.32)

Complete-case development sample (n=8,623; 678 readmissions). Combined estimates in the second block were derived from 20 multiple imputations of missing Clinical Frailty Scale values in the eligible cohort (n=10,169; 799 readmissions), with coefficients and variances combined using Rubin's rules; the single record with missing admission SOFA was completed by matched donor selection. The imputation used an ordinal logistic model and not multiple imputation by chained equations. p values refer to the complete-case model. Reference categories: female sex, operating room origin, emergency surgical admission, non-SUS payer source. Apparent AUCs were 0.6159 (complete-case) and 0.6103 (imputed); these are descriptive estimates obtained in different analytic samples and are not optimism-corrected comparisons. OR: odds ratio; CI: confidence interval; SOFA: Sequential Organ Failure Assessment; SUS: Brazilian Unified Health System.

Source: Prepared by the authors (2026).

benefit of zero throughout the threshold range.

The alternative model added discharge SOFA and ICU length of stay to the main model (Table 5). Both were independent predictors (OR 1.18; 95% CI 1.14–1.22; p<0.001 and OR 1.01; 95% CI 1.00–1.01; p=0.010, respectively). Its apparent AUC was 0.6216 (95% CI 0.5997–0.6436), with AIC 4,571.9 and Tjur coefficient 0.0278. The gain in discrimination over the main model was negligible (0.0057), with widely overlapping AUC confidence intervals (0.5997–0.6436 vs 0.5943–0.6375). Because discharge SOFA and length of stay are available only at the end of the ICU stay, the main model was retained as the reference for the CDSS, as its predictors are all available at admission and therefore compatible with early risk stratification and transition-of-care planning.

Risk strata were defined post hoc based on the predicted probability of the main model. The observed unplanned ICU readmission rate increased across these strata: 4.3% (62/1,449; 95% CI, 3.4–5.4%) in the low-risk group, 7.7% (413/5,398; 95% CI, 7.0–8.4%) in the intermediate-risk group, and 11.4% (203/1,776; 95% CI, 10.0–13.0%) in the high-risk group (Table 6). These categories were defined post hoc in the development cohort for risk communication and should not be interpreted as validated clinical decision thresholds;

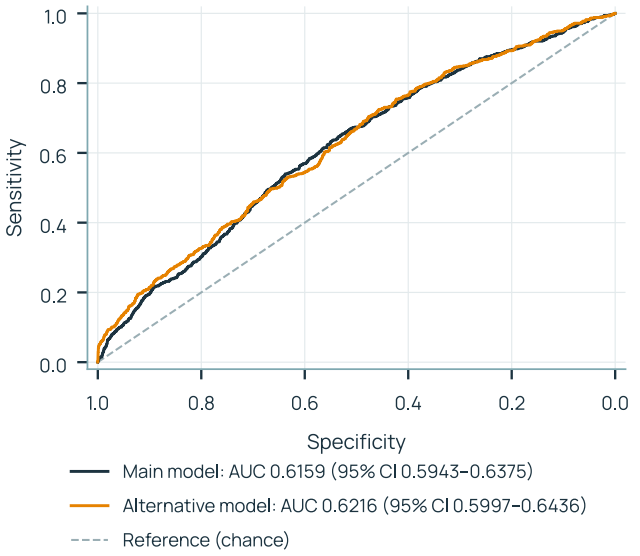
Table 4. Full logistic regression equation and coefficients.

Variable	Coefficient β	Standard error	OR (eβ)
Intercept	-3.600	0.238	—
Age (Years)	0.00705	0.00271	1.007
Sex (male)	0.202	0.0817	1.224
Frailty (CFS)	0.0485	0.0294	1.050
SOFA admission	0.0734	0.0135	1.076
Origin: Ward	0.536	0.144	1.709
Origin: Hemodynamics unit	0.406	0.161	1.501
Origin: Emergency department	0.336	0.103	1.399
Elective surgical admission	-0.275	0.155	0.760
Medical admission	-0.0667	0.144	0.936
Payer source: Brazilian Unified Health System (SUS)	0.119	0.0844	1.126

Complete-case development sample (n=8,623; 678 readmissions). OR: odds ratio; CFS: Clinical Frailty Scale; SOFA: Sequential Organ Failure Assessment; SUS: Brazilian Unified Health System. Reference categories: female sex, operating room admission source, emergency surgical admission and non-SUS payer source.

Source: Prepared by the authors (2026).

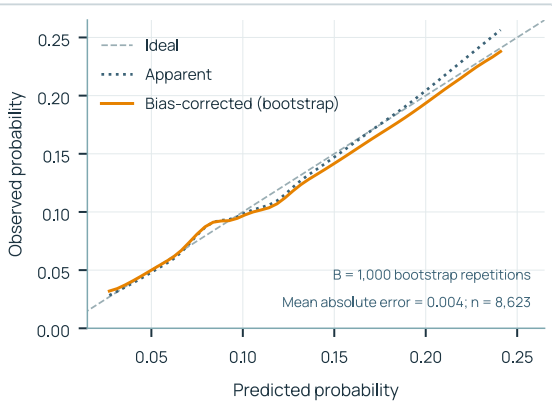
Figure 2. Receiver Operating Characteristic (ROC) curves for the prediction of unplanned ICU readmission within seven days.



The graph displays the discriminative performance of the main model (prespecified predictors) and the alternative model (including discharge SOFA and length of stay). The dark blue curve refers to the main model, which presented an area under the curve (AUC) of 0.6159 (95% CI: 0.5943–0.6375). The orange curve represents the alternative model, with an AUC of 0.6216 (95% CI: 0.5997–0.6436).

Source: Prepared by the authors (2026).

Figure 3. Calibration plot of the logistic regression model for predicting 7-day unplanned ICU readmission.



The bias-corrected curve follows the ideal diagonal across the 0.05–0.20 probability range, with a mean absolute error of 0.004 and a corrected Brier score of 0.0717, indicating adequate calibration but weak discrimination and only marginal improvement in overall probabilistic performance over the baseline event rate.

Source: Prepared by the authors (2026).

recalibration is required before use in other populations.

The CDSS was implemented as an interactive web application ("Early Risk Stratification for Unplanned ICU Readmission"), organized into three tabs and accessible at https://cepetitecnologia.shinyapps.io/app_readmissao/. The Risk Calculator tab computes the predicted probability of 7-day readmission in real time from manually entered predictors, displaying it alongside a traffic-light classification (green, amber, red), a suggested interpretation for transition-of-care planning, and the observed readmission rate of the corresponding stratum. The About tab describes the purpose, target population and operational instructions, while the Performance tab displays the ROC curve, calibration plot, apparent and optimism-corrected AUC, Brier score, mean absolute error and observed event rates by stratum. The responsive application runs in standard web browsers, requires no local installation or EHR integration, and adapts to smartphones, tablets and desktop computers. Across 100 records, the maximum absolute difference between predictions from the original fitted model and the reproduced application workflow was 9.71×10^{-17} (mean absolute difference, 1.44×10^{-17}); against the independent full-precision equation, the maximum and mean absolute differences were 2.78×10^{-17} and 6.04×10^{-18}, respectively. All predictions agreed within the prespecified tolerance of 10^{-10}, and risk-stratum classification agreed in 100 of 100 records. This assessment verified the numerical consistency of the implemented calculation and does not constitute end-to-end user-interface testing or external clinical validation.

Table 5. Alternative logistic regression model including discharge SOFA and length of stay.

Predictor	Adjusted OR	95% CI	p value
Age (years)	1.01	1.00–1.01	0.018
Sex	1.17	0.99–1.37	0.061
Clinical Frailty Scale	1.01	0.96–1.07	0.7
Discharge SOFA	1.18	1.14–1.22	<0.001
Length of stay (days)	1.01	1.00–1.01	0.010
Admission source			
Operating room (reference)	1	-	-
Ward	1.64	1.23–2.18	<0.001
Hemodynamics unit	1.48	1.07–2.03	0.015
Emergency department	1.39	1.14–1.71	0.001
Type of admission			
Emergency surgical (reference)	1	-	-
Elective surgical	0.77	0.57–1.05	0.091
Medical	0.88	0.66–1.17	0.4
Payer source	1.11	0.94 -1.30	0.2

Complete-case development sample (n=8,623). OR: odds ratio. CI: confidence interval. SOFA: Sequential Organ Failure Assessment.

Source: Prepared by the authors (2026).

Table 6. Observed unplanned ICU readmission rates by risk stratum.

Risk stratum	Readmissions / N	Observed rate	95% CI (Wilson)
Low (<5%)	62 / 1,449	4.3%	3.4–5.4%
Intermediate (5–<10%)	413 / 5,398	7.7%	7.0–8.4%
High (≥10%)	203 / 1,776	11.4%	10.0–13.0%
Total	678 / 8,623	7.9%	7.3–8.4%

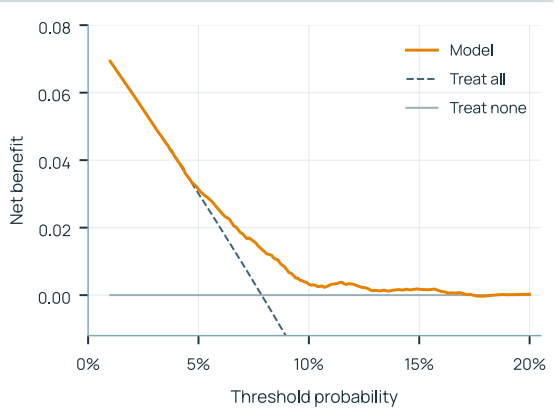
Complete-case development sample (n=8,623). CI: confidence interval.

Source: Prepared by the authors (2026).

Usability evaluation was conducted in two phases, as described in Section 2.6. In the first phase, the preliminary CDSS interface underwent heuristic inspection based on Nielsen's ten usability heuristics [31]. The inspection identified opportunities for adjustment mainly related to the heuristics of visibility of system status, match between system and the real world, flexibility and efficiency of use, and aesthetic and minimalist design. The adjustments implemented were: increased font size, to improve readability on mobile devices; redesign of the interface's visual layout; adjustment of the three-color traffic-light scale that displays the low, intermediate and high risk strata; configuration of the buttons to speed up data entry; and reordering of screen elements, so that the data entry sequence follows the flow of clinical reasoning. These changes were incorporated into the version of the system assessed in the second phase, the usability test with end users, described below.

A qualitative usability pilot with five physicians using the Think Aloud method suggested that the traffic-light visualization, the single-screen layout and the independence from the EHR favored rapid interpretation during rounds; participants proposed refinements to label terminology and entry-field tolerance for subsequent iterations. Participants were three intensivists and two residents, with a median of 7 years of ICU experience (range 6–9). All reported frequent or daily use of decision-support tools. The mean SUSc score was 99.5 (SD 1.1; range 97.5–100; median 100), and every score was in grade A. Responses varied in only one SUSc item, confidence in using the system (mean 4.8). Clarity of the risk estimate and independence from the EHR both scored 5.0, and perceived speed of decision-making scored 4.4 (range 4–5). Scores clustered at the upper limit of the scale, characterizing a ceiling effect: the instrument could not discriminate differences in perceived usability within this sample, and the narrow dispersion should be read as an absence of detected barriers rather than as evidence of exceptionally high usability.

Figure 4. Decision curve analysis of the primary prediction model for unplanned ICU readmission within seven days.



Net benefit is shown across threshold probabilities for the prediction model and the reference strategies of intervening in all patients (treat-all) or in no patients (treat-none). The model demonstrated a positive but modest net benefit across clinically relevant threshold probabilities, with a greater relative advantage over the treat-all strategy at thresholds above approximately 5%.

Source: Prepared by the authors (2026).

4 DISCUSSION

The principal contribution of this study is the development, internal validation and bedside operationalization of a parsimonious model for unplanned seven-day ICU readmission in a Brazilian multicenter cohort. Rather than pursuing high accuracy, intrinsically limited in unselected cohorts, we deliver a transparent, web-based CDSS for screening and transition planning, with effect sizes compatible with the literature [1,2,4,5]. Traditional severity and resource-use markers, such as higher APACHE II and longer ICU stay, were associated with readmission in bivariate analysis [2,5,6] but were not retained in the final model. Admission SOFA, ward origin, male sex and older age were the sole independent predictors, since physiological derangement and prolonged hospitalization correlate with risk in unadjusted analyses but do not drive the tool's performance once baseline characteristics and admission dynamics are accounted for. These findings align with prior machine-learning studies [7], and the higher frequency of SUS as payer source adds contextual specificity for the Brazilian setting [18]. Homogeneity between early and late readmission subgroups suggests vulnerability is established early in the critical illness trajectory, supporting an admission-based model.

Binary logistic regression was chosen for interpretive transparency, since auditability of the decision criterion is essential to incorporating decision support into routine care [14], and its coefficients allow the intensivist to weigh each variable's contribution to risk [15]. Predictors were prespecified without univariate screening, following TRIPOD recommendations, and variables that did not reach significance were retained because individual p values are not decisive in prediction modeling [15,16]. APACHE II was excluded for conceptual overlap with age and admission SOFA, prioritized for its dynamic nature and parsimony [24].

Although the apparent AUC is below thresholds for confirmatory diagnostics, it is consistent with models addressing multifactorial, low-prevalence outcomes [4, 9]; for stratification rather than diagnosis, this magnitude retains value when accompanied by adequate calibration [15,32]. Calibration was adequate, but the information gain over the baseline rate was marginal, and the Tjur coefficient and the corrected AUC denote weak discrimination: clinical value lies in ranking into actionable strata, not in individual accuracy. The gap between the AUC assumed in planning and that obtained shows the prior expectation was optimistic; because the sample far exceeded the calculated minimum, power was preserved. Decision curve analysis showed a positive but small net benefit, largely equivalent to treating all at the lowest thresholds and favoring the model as thresholds increased, indicating value in avoiding unnecessary intervention rather than in improving accuracy overall. Meta-analytic evidence indicates that complex machine-learning models frequently provide gains that do not offset the loss of transparency and practical utility in multifactorial problems without a dominant predictor [33].

Although the alternative model showed a marginally lower AIC and a higher Tjur coefficient, the difference in discrimination was small and not clinically meaningful, and the post hoc cut-offs were defined as actionable categories [16]. Being EHR-independent, the CDSS allows risk query from any device and use across units of differing digital maturity; using R for modeling and implementation ensures the executed equations match the estimated parameters, and the performance tab displays ROC and calibration curves with AUC confidence intervals [13]. The mobile-first design fits the bedside workflow, and the Think Aloud evaluation indicated that the traffic-light display favors rapid interpretation, reducing cognitive load [10].

Nevertheless, this study has limitations. Most importantly, the model lacks external validation and prospective evaluation, so its clinical utility and impact on outcomes remain undemonstrated [16]. Complete-case analysis excluded 15.2% of eligible patients, mostly for missing Clinical Frailty Scale assessments; although included and excluded patients differed only marginally (all absolute SMDs <0.10), residual selection bias cannot be excluded, and multiple imputation yielded broadly similar estimates without ruling out departures from the missing-at-random assumption. The risk strata were defined post hoc and require recalibration elsewhere [16]. Admission-time variables do not capture intercurrent events or late nosocomial infections [15]. Finally, the retrospective design introduces measurement bias, particularly for physician-reported measures such as the frailty scale

[5], and functional capacity was rated on a study-specific scale not externally validated. Because predictor values are entered manually, transcription errors and misclassification of categorical variables are possible; the numerical agreement between the equation and the implemented workflow demonstrates computational fidelity, not data-entry accuracy.

5 CONCLUSION

This study developed, internally validated and implemented as a web tool a parsimonious, interpretable model for stratifying seven-day unplanned ICU readmission risk in a Brazilian multicenter cohort. Given limited discrimination, adequate calibration and modest net benefit, the model ranks patients into risk strata rather than identifying high-risk individuals. Its transparency, independence from the electronic health record and high usability at the bedside make it a complementary instrument for transition-of-care planning in units of differing digital maturity. It should not be used as a stand-alone decision tool until external and prospective validation demonstrates an effect on outcomes.

Author contributions. Altemar dos Santos Paigel, Rafaella Stradiotto Bernardelli, Álvaro Réa-Neto and Sergio Ossamu Ioshi contributed to the conception and design of the study. Altemar dos Santos Paigel, Rafaella Stradiotto Bernardelli and Marcelo José Martins Junior contributed to data collection. Rafaella Stradiotto Bernardelli and Marcelo José Martins Junior performed the statistical analysis. Jeane Cristina Fonseca Vieira, Marcelo José Martins Junior and Isadora Celine Rodrigues Carneiro Camargo performed the clinical review of the cases and supported the usability test. All authors contributed to the interpretation of the data, to the drafting and critical revision of the manuscript, and approved the final version. All authors agree to be accountable for all aspects of the work, ensuring that questions related to the accuracy or integrity of any part of the study are appropriately investigated and resolved.

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Data and materials availability. The de-identified dataset is not publicly available because it is owned by the five participating institutions and its sharing is restricted by the Brazilian General Data Protection Law; it may be obtained from the corresponding author on reasonable request, subject to Research Ethics Committee approval and a data use agreement. The full regression coefficients are reported in Table 4, allowing model reproduction without individual-level data. The source code is available from the corresponding author on request. The application contains no patient-level data and is freely accessible at https://cepetitecnologia.shinyapps.io/app_readmissao/.

Conflicts of interest. The authors declare no conflicts of interest.

Use of artificial intelligence. Artificial intelligence tools (Claude Opus 4.7) were used only for language editing and formatting of the manuscript. No content, data analysis or interpretation of results was generated by artificial intelligence. The authors are fully responsible for the scientific content of the manuscript.

REFERENCES

1. Hosein FS, Roberts DJ, Turin TC, Zygun D, Ghali WA, Stelfox HT. A meta-analysis to derive literature-based benchmarks for readmission and hospital mortality after patient discharge from intensive care. Crit Care. 2014;18(6):715. doi: https://doi.org/10.1186/s13054-014-0715-6
2. Ponzoni CR, Corrêa TD, Filho RR, Serpa Neto A, Assunção MSC, Pardini A, et al. Readmission to the Intensive Care Unit: Incidence, Risk Factors, Resource Use, and Outcomes. A Retrospective Cohort Study. Ann Am Thorac Soc. 2017;14(8):1312-9. doi: https://doi.org/10.1513/annalsats.201611-851oc
3. McNeill H, Khairat S. Impact of Intensive Care Unit Readmissions on Patient Outcomes and the Evaluation of the National Early Warning Score to Prevent Readmissions: Literature Review. JMIR Perioper Med. 2020;3(1):e13782. doi: https://doi.org/10.2196/13782
4. Long J, Wang M, Li W, Cheng J, Yuan M, Zhong M, et al. The risk assessment tool for intensive care unit readmission: A systematic review and meta-analysis. Intensive Crit Care Nurs. 2023;76:103378. doi: https://doi.org/10.1016/j.iccn.2022.103378
5. Pilowsky JK, von Huben A, Elliott R, Roche MA. Development and validation of a risk score to predict unplanned hospital readmissions in ICU survivors: A data linkage study. Aust Crit Care. 2024;37(3):383-90. doi: https://doi.org/10.1016/j.aucc.2023.05.002
6. Yin YL, Sun MR, Zhang K, Chen YH, Zhang J, Zhang SK, et al. Status and Risk Factors in Patients Requiring Unplanned Intensive Care Unit Readmission Within 48 Hours: A Retrospective Propensity-Matched Study in China. Risk Manag Healthc Policy. 2023;16:383-91. doi: https://doi.org/10.2147/rmhp.s399829
7. Desautels T, Das R, Calvert J, Trivedi M, Summers C, Wales DJ, et al. Prediction of early unplanned intensive care unit readmission in a UK tertiary care hospital: a cross-sectional machine learning approach. BMJ Open. 2017;7(9):e017199. doi: https://doi.org/10.1136/bmjopen-2017-017199
8. Lin YW, Zhou Y, Faghri F, Shaw MJ, Campbell RH. Analysis and prediction of unplanned intensive care unit readmission using recurrent neural networks with long short-term memory. PLoS One. 2019;14(7):e0218942. doi: https://doi.org/10.1371/journal.pone.0218942

9. Koumantakis E, Remoundou K, Colombi N, Fava C, Roussaki I, Visconti A, et al. Deep learning models for ICU readmission prediction: a systematic review and meta-analysis. Crit Care. 2025;29(1):442. doi: https://doi.org/10.1186/s13054-025-05642-x
10. Carayon P, Hoonakker P. Human Factors and Usability for Health Information Technology: Old and New Challenges. Yearb Med Inform. 2019;28(01):71-7. doi: https://doi.org/10.1055/s-0039-1677907
11. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56. doi: https://doi.org/10.1038/s41591-018-0300-7
12. Rivabem FS, Faleiros Júnior JLM. Transformação digital no Sistema Único de Saúde: interoperabilidade, governança e proteção de dados sensíveis. Rev Direito Sanit. 2025;25(1):e0011. doi: https://doi.org/10.11606/issn.2316-9044.rdisan.2025.231455
13. Kawamoto K, Houlihan CA, Balas EA, Lobach DF. Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. BMJ. 2005;330(7494):765. doi: https://doi.org/10.1136/bmj.38398.500764.8f
14. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. NPJ Digit Med. 2020;3(1):17. doi: https://doi.org/10.1038/s41746-020-0221-y
15. Steyerberg EW. Clinical prediction models: a practical approach to development, validation, and updating. 2nd ed. Cham: Springer; 2019. doi:10.1007/978-3-030-16399-0
16. Collins GS, Reitsma JB, Altman DG, Moons KGM. Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD): The TRIPOD Statement. Ann Intern Med. 2015;162(1):55-63. doi: https://doi.org/10.7326/m14-0697
17. Riley RD, Snell KI, Ensor J, Burke DL, Harrell Jr FE, Moons KG, et al. Minimum sample size for developing a multivariable prediction model: PART II - binary and time-to-event outcomes. Stat Med. 2019;38(7):1276-96. doi: https://doi.org/10.1002/sim.7992
18. Nogueira LS, Sousa RMC, Padilha KG, Koike KM. Características clínicas e gravidade de pacientes internados em UTIs públicas e privadas. Texto Contexto Enferm. 2012;21(1):59-67. doi: https://doi.org/10.1590/s0104-07072012000100007
19. Haruna J, Masuda Y, Tatsumi H. Transitional Care Programs for Patients with High Nursing Activity Scores Reduce Unplanned Readmissions to Intensive Care Units. Medicina (Kaunas). 2022;58(11):1532. doi: https://doi.org/10.3390/medicina58111532
20. Österlind J, Gerhardsson J, Myrberg T. Critical care transition programs on readmission or death: A systematic review and meta-analysis. Acta Anaesthesiol Scand. 2020;64(7):870-83. doi: https://doi.org/10.1111/aas.13591
21. Rockwood K, Theou O. Using the Clinical Frailty Scale in Allocating Scarce Health Care Resources. Can Geriatr J. 2020;23(3):254-9. doi: https://doi.org/10.5770/cgj.23.463
22. Knaus WA, Draper EA, Wagner DP, Zimmerman JE. APACHE II. Crit Care Med. 1985;13(10):818-29. doi: https://doi.org/10.1097/00003246-198510000-00009
23. Vincent JL, Moreno R, Takala J, Willatts S, De Mendonça A, Bruining H, et al. The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure. Intensive Care Med. 1996;22(7):707-10. doi: https://doi.org/10.1007/bf01709751
24. Ferreira FL. Serial Evaluation of the SOFA Score to Predict Outcome in Critically Ill Patients. JAMA. 2001;286(14):1754. doi: https://doi.org/10.1001/jama.286.14.1754
25. Wickham H. Mastering Shiny: build interactive apps, reports, and dashboards powered by R. Sebastopol: O'Reilly Media; 2021. Available from: https://mastering-shiny.org
26. Jaspers MWM. A comparison of usability methods for testing interactive health technologies: Methodological aspects and empirical evidence. Int J Med Inform. 2009;78(5):340-53. doi: https://doi.org/10.1016/j.ijmedinf.2008.10.002
27. van den Haak M, De Jong M, Schellens PJ. Retrospective vs. concurrent think-aloud protocols: Testing the usability of an online library catalogue. Behav Inf Technol. 2003;22(5):339-51. doi: https://doi.org/10.1080/0044929031000
28. Nielsen J. Why you only need to test with 5 users [Internet]. Fremont: Nielsen Norman Group; 2000 [cited 2026 May 11]. Available from: https://www.nngroup.com/articles/why-you-only-need-to-test-with-5-users/
29. Brooke J. SUS: a "quick and dirty" usability scale. In: Jordan PW, Thomas B, Weerdmeester BA, McClelland IL, editors. Usability evaluation in industry. London: Taylor & Francis; 1996. p. 189-94.
30. Sauro J, Lewis JR. Quantifying the user experience: practical statistics for user research. 2nd ed. Cambridge: Morgan Kaufmann; 2016.
31. Nielsen J. Usability engineering. Boston: Academic Press; 1993.
32. Hosmer DW, Lemeshow S, Sturdivant RX. Applied logistic regression. 3rd ed. Hoboken: Wiley; 2013. doi: 10.1002/9781118548387
33. Talwar A, Lopez-Olivo MA, Huang Y, Ying L, Aparasu RR. Performance of advanced machine learning algorithms over logistic regression in predicting hospital readmissions: A meta-analysis. Explor Res Clin Soc Pharm. 2023;11:100317. doi: https://doi.org/10.1016/j.rcsop.2023.100317

EDITORIAL NOTES

The Journal of Health Informatics is a scientific journal maintained by the Brazilian Society of Health Informatics (Sociedade Brasileira de Informática em Saúde), a non-profit scientific association dedicated to the development of Health Informatics and Digital Health in Brazil. The editorial process is conducted with scientific independence, free from institutional, commercial, or sponsor interference, and follows international best practices in publication ethics.

This article was double-blind peer reviewed by specialists in the field. The editorial team used artificial intelligence tools, under human supervision, in the initial screening, in checking the text, references and numbers and, when needed, in redrawing figures, charts and tables, which the authors approved in the proof. The tools and safeguards are described in the journal's Policy on the use of artificial intelligence. Editorial decisions were made by people.

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