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VALIDATION OF A DYNAMIC RISK CLASSIFICATION SYSTEM FOR IN-HOSPITAL DEATH, BASED ON ELECTRONIC RECORDS OF NON-SURGICAL ADMISSIONS TO GENERAL HOSPITALS

VALIDAÇÃO DE UMA CLASSIFICAÇÃO DE RISCO DINÂMICA PARA ÓBITO HOSPITALAR, BASEADA EM PRONTUÁRIOS ELETRÔNICOS DE INTERNAÇÕES NÃO-CIRÚRGICAS EM HOSPITAIS GERAIS

VALIDACIÓN DE UMA CLASIFICACIÓN DE RIESGO DINAMICA PARA DEFUNCIÓN HOSPITALARIA, BASADA EN REGISTROS ELECTRONICOS DE ADMISIONES NO-QURÚRGICAS EN HOSPITALES GENERALES

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ABSTRACT

Objective: To develop and validate a risk-classification system for in-hospital death for general hospital non-surgical cases. **Methods:** Admissions at 5 public general hospitals of Minas Gerais were included. A predictive model for death during admission was built using logistic regression. A severity index was created and its ability to predict in-hospital death during index admission validated. **Theoretical foundation**: Usually, predictive models focus on a specific disease or condition, instead of the totality of admitted patients. **Results:** The final multivariate model included seven significant predictive variables: age, gender, diagnostic-related group, hospital of index admission, admission to the ICU, total length of stay, and unplanned surgical procedure. This model presented adequate fit and fair discriminative performance (AUC=0.78). Temporal validation with a new sample also presented an adequate fit, and the discriminative performance was again fair (AUC=0.76). **Conclusions:** A dynamic and clinically useful risk classification system for in-hospital death of non-surgical admissions has been validated.

Key-words: in-hospital mortality; risk management; electronic health records

RESUMO

Objetivo: Desenvolver e validar um sistema de classificação de risco para óbito hospitalar, em hospitais gerais, em casos não cirúrgicos. **Métodos:** Foram incluídas internações em 5 hospitais gerais públicos de Minas Gerais. Um modelo preditivo de óbito hospitalar foi construído por meio de regressão logística. Um índice de gravidade foi criado e sua capacidade de prever a morte intra-hospitalar durante a admissão índice foi validada. **Fundamentação teórica:** Normalmente, os modelos preditivos enfocam uma doença ou condição específica, em vez da totalidade dos pacientes internados. **Resultados:** O modelo multivariado final incluiu sete variáveis preditivas significativas: idade, sexo, grupo relacionado ao diagnóstico, hospital de admissão, admissão à UTI, tempo total de internação e cirurgia não planejado. Este modelo apresentou ajuste adequado e desempenho discriminativo regular (AUC = 0,78). A validação temporal com uma nova amostra também apresentou um ajuste adequado e o desempenho discriminativo foi novamente regular (AUC = 0,76). **Conclusões:** Um sistema de classificação de risco dinâmico e clinicamente útil para óbito hospitalar de internações não-cirúrgicas foi validado.

Palavras-chave: Mortalidade Intra-Hospitalar; Gerenciamento de Risco; Prontuários Eletrônicos do Paciente

RESUMEN

Objetivo: Desarrollar y validar un sistema de clasificación de riesgo de muerte intrahospitalaria, para casos no quirúrgicos en hospitales generales. **Métodos:** Se incluyeron ingresos en 5 hospitales generales públicos de Minas Gerais. Un modelo predictivo de muerte durante el ingreso fue creado utilizando regresión logística. Se creó un índice de gravedad y su capacidad para predecir la muerte intrahospitalaria fue validada. **Fundamento teórico:** Por lo general, los modelos predictivos se centran en una enfermedad específica y no en la totalidad de los pacientes ingresados. **Resultados:** El modelo multivariado final incluyó siete variables predictivas significativas: edad, sexo, grupo relacionado con el diagnóstico, hospital de admisión índice, ingreso en UCI, tiempo total de estadía y cirugía no planeada. Este modelo presentó un ajuste adecuado y un desempeño discriminativo regular (AUC = 0,78). La validación temporal con una nueva muestra también presentó un ajuste adecuado y el desempeño discriminativo fue regular (AUC = 0,76). **Conclusiones:** Se ha validado un sistema de clasificación de riesgo dinámico y clínicamente útil para la muerte intrahospitalaria de admisiones no quirúrgicas.

Palabras-clave: Mortalidad Hospitalaria; Gestión de Riesgos; Registros Electrónicos de Salud

INTRODUCTION AND THEORETICAL FOUNDATIONS

The primary mission of health institutions is to perform interventions to prevent or delay death. Risk factors for death are sources of information for guiding the implementation of models of care, health promotion, prevention and control actions. Dynamically assessing those risk factors allows the adoption of immediate strategies aimed at increasing the possibility of survival, and consequently, the reduction of lethality.

Despite all efforts, hospitals are currently the place of deceasing in nearly two-thirds of the deaths in Brazil (BRAZIL, s.d).

Brazilian universal public health system is hierarchically designed, and the state of Minas Gerais follows the same directives: family health programs provide primary healthcare (covering almost 90% of the state's population), stationary emergency units provide pre-hospital care, and when a hospital admission is required, patients are referred by an integrated regulation system to the next available hospital bed (BRAZIL, 2010). Public general hospitals of Minas Gerais also admit self-referred patients, especially for surgical procedures or complications of chronic diseases.

By monitoring risk factors for unfavorable outcomes, health institutions favor quality through while improving clinical governance (WHO/OCDE/WB, 2018). Focusing on the detection of sources of vulnerability and on the severity and complexity of the health conditions are essential aspects of quality of healthcare. Identifying the risk factors for unfavorable outcomes is, thus, a major and obvious priority for health services.

In the specific context of hospital care, and based on identifiable risk factors, practical tools might be developed in order to better predict potentially fatal outcomes and timely make the necessary adjustments in care.

Usually, predictive models focus on a specific disease or condition, instead of the totality of admitted patients. However, if the goal is to develop clinical tools for adjusting the interventions to reduce risks in the institution as a whole, a more holistic approach seems favorable. In Brazil, only Gomes et al. (2010) have performed multilevel analyses of the risk factors for mortality in public hospitals, in the state Rio Grande do Sul. On the individual level, only age and admission to the ICU were significant factors, however, the availability of variables was limited due to the use of a national administrative registry, instead of more detailed hospital records. The quite recent availability of electronic health records present a novel scenario in Brazil, where big datasets can be analyzed for clinically meaningful information.

In the present paper, we aimed at assessing the risk factors for inpatient death in public state general hospitals of Minas Gerais, by extracting relevant clinical information from the hospitals' health information system. We then developed and validated a classification of risk of in-hospital death, using a severity index based on those results.

METHODS

This is an observational study based on electronic health records.

Data was gathered from the 5 public general hospitals administered by the Hospital Foundation of Minas Gerais, Brazil. All hospitals are equipped with intensive care units (ICU), and have an open access emergency room. The number of beds varies from 75 in the smaller hospital, to 369 in the largest.

Initially, all hospitalizations initiated from Jan 1st to Dec 31st 2016, for non-surgical conditions- as defined at the moment of admission- were included. Then, psychiatric and obstetric diagnoses (ICD-10 chapters XV, XVI, XVII) were excluded from the sample, as well as pediatric cases (<18 years-old at admission).

Computerized data mining was used to analyze e-health records. The outcome binary variable was death during index admission. Predictor variables included: 1) patient-related (age, gender, marital status, schooling, place of residence in the same hospital's city, main diagnosis at admission, and comorbidities); and 2) admission characteristics (hospital of index admission, elective or emergency admission, length of stay, admission to the ICU, and unplanned surgery- since some clinical cases underwent surgery during the index admission).

In order to reduce the number of categories, original ICD-10 diagnoses were recoded according to Diagnostic Related Groups classification (DRG; v. 33, Centers for Medicare & Medicaid Services [s.d.]). For the purposes of this study, the 20 more frequent DRGs in the index year (2016) were individually discriminated (56% of the sample), the remaining being designated as a residual category.

Comorbidities were extracted using data mining on open fields of medical records, and included smoking and drinking status, hypertension and diabetes mellitus. Anthropometric data was irregularly registered, thus, obesity could not be verified. Data on schooling and marital status were missing for 78% and 29% of the records, so those variables had to be discarded.

Analyses:

The first goal was to build a predictive model for death during admission, estimating the independent magnitude of effects for each predictor variable. This was executed in the index 1-year sample (2016) in two steps:

1) For bivariate analyses, binary logistic regressions were performed for each of the discrete predictor variables against the outcome variable (death during index admission), and Student t- or Kruskal-Wallis tests to compare means/medians of each continuous variables according to the outcome.

2) Only predictor variables presenting p-values <0.20 on bivariate analyses were included in a multiple binary logistic regression using a backward stepwise strategy using the Akaike information criteria and a 5% significance level. Admissions containing missing values were excluded.

Once a final model was built, we aimed at creating a severity index based on the independent effect of the selected variables, and then, at validating its ability to predict in-hospital death during index admission. Hosmer-Lemeshow tests were performed to assess the goodness-of-fit of the model. A receiver-operating characteristic curve (ROC) analysis was performed to estimate the overall discriminative performance of the model, by calculating the area under the curve (AUC). Also, for each observation, the event probability was estimated. This probability was then analyzed separately for the fatal and non-fatal outcome groups, and cutoff points for risk classification were defined using the 2^{nd}- and the 3^{rd}-quartile limits of each group, resulting in a 5-classes system.

Aiming at external validation, we challenged the predictive model with a new dataset, using the same inclusion/exclusion criteria, but selecting admissions occurred in the subsequent year (2017) in the same hospitals. This procedure is known as temporal validation. Again, estimated event probabilities were compared to actual outcomes using ROC (AUC), and Hosmer-Lemeshow tests were performed.

All analyses were performed using MINITAB v.16. ROC analyses used ROCBLR macro (MINITAB, 2019).

RESULTS

In 2016, a total of 19,468 admissions were recorded on the 5 general hospitals, 8,927 of which were primarily non-surgical admissions.

Table 1 displays the descriptive features of the sample, and the results of bivariate analyses. Table 2 shows the 20 more prevalent DRGs.

Of the selected variables, only smoking and drinking status did not reach the bivariate significance level for entering the multivariate model.

The final multivariate model included seven significant predictive variables of in-hospital death: age, gender, DRG, hospital of index admission, admission to the ICU, total length of stay, and unplanned surgical procedure (Table 3). Admission to the ICU and HIV-related diagnoses were the most relevant risk factors, in terms of magnitude of the associations.

Table 1 – Comparative analyses of demographic and clinical variables of non-surgical admissions to general hospitals in 2016.

Variable	All admissions (N=4998)		In-hospital death (N=685)		Discharged (N=4313)		p
	N	%	N	%	N	%	
Age *(mean±sd)*	*60.5±18.2*		*66.1±17.5*		*59.6±18.1*		<0.001
Male	2693	53.9	388	56.6	2305	53.4	0.119
Place of residence							
Same city	3512	70.3	447	65.3	3065	71.1	0.002
Other city	1486	29.7	238	34.7	1248	28.9	
Diabetes mellitus	731	14.6	114	16.6	617	14.3	0.108
Hypertension	1963	39.3	327	47.7	1636	37.9	<0.001
Smoking status							
Active	1189	23.8	147	21.5	1042	24.2	0.293
Quitter	910	18.2	126	18.4	784	18.2	
Never	2899	58.0	412	60.2	2487	57.7	
Alcohol abuse							
Active	1182	23.7	159	23.2	1023	23.7	0.871
Quitter	546	10.9	72	10.5	474	11.0	
Never	3270	65.4	454	66.3	2816	65.3	
Type of admission							
Elective	701	14.1	79	11.5	622	14.4	0.043
Emergency	4297	85.9	606	88.5	3691	85.6	
Lenght of stay							
0-3 d	985	19.7	141	20.6	844	19.6	<0.001
4-7 d	1195	23.9	144	21.0	1051	24.4	
8-14 d	1377	27.6	134	19.6	1243	28.8	
15-374 d	1441	28.8	266	38.8	1175	27.2	
Admitted to the ICU	466	9.3	234	34.2	232	5.4	<0.001
	373	7.5	108	15.8	265	6.1	<0.001
Hospital							
H1	821	16.4	105	15.3	716	16.6	<0.001
H2	676	13.5	122	17.8	554	12.8	
H3	2223	44.5	267	40.0	1956	45.4	
H4	585	11.7	114	16.6	471	10.9	
H5	693	13.9	77	11.2	616	14.3	

Source: Authors' data analyses.

Table 2 – Twenty more prevalent Diagnostic Related Groups (DRG) of non-surgical admissions to general hospitals, 2016.

DRG	Description	N	%
177-179	Respiratory Infections and Inflammations	545	10.90
391-392	Esophagitis, Gastroenteritis and Miscellaneous Digestive Disorders	503	10.06
064-066	Intracranial Hemorrhage or Cerebral Infarction	399	7.98
190-192	Chronic Obstructive Pulmonary Disease	357	7.14
637-639	Diabetes	349	6.98
204	Respiratory Signs and Symptoms	314	6.28
291-293	Heart Failure and Shock	297	5.94
193-195	Simple Pneumonia and Pleurisy	265	5.30
304-305	Hypertension	236	4.72
865-866	Viral Illness	207	4.14
308-310	Cardiac Arrhythmia and Conduction Disorders	199	3.98
811-812	Red Blood Cell Disorders	189	3.78
689-690	Kidney and Urinary Tract Infections	171	3.42
377-379	G.I.Hemorrhage	168	3.36
299-301	Peripheral Vascular Disorders	166	3.32
444-446	Disorders of Biliary Tract	141	2.82
432-434	Other Hepatobiliary or Pancreas Procedures	131	2.62
602-603	Cellulitis	124	2.48
313	Chest Pain	119	2.38
969-977	Human Immunodeficiency Virus Infections	118	2.36

Source: Authors' data analyses.

Table 3 – Multivariate analyses of risk factors for in-hospital death among non-surgical admissions to general hospitals, 2016. (N=4998)

Variable		Coefficient	OR (95% CI)*	p
Hospital				<0.001
	H1	-0.434795	0.64 (0.48-0.85)[a]	
	H2	-0.263871	0.76 (0.54-1.08)[a c]	
	H3	-0.348148	0.70 (0.50-0.98)[a]	
	H4	-0.905756	0.40 (0.27-0.58)[b]	
	H5		1[c]	
Age		0.0318494	1.03 (1.02-1.03)	<0.001
Gender		0.187915		<0.047
	male		1.20(1.01-1.45)	
	female		1	
Lenght of stay				<0.001
	0-3 d	0.863408	2.37 (1.78-3.15)[a]	
	4-7 d	0.42476	1.52 (1.16-2.00)[b]	
	8-14 d		1[c]	
	15-374 d	0.123463	1.13 (0.87-1.46)[c]	

Conclusion

Variable		Coefficient	OR (95% CI)*	p
Admitted to the ICU		2.33712	10.35 (8.00-13.38)	<0.001
DRG				<0.001
	064-066		0.07 (0.04-0.12)[a]	
	177-179	1.00352	0.19 (0.12-0.32)[b]	
	190-192	0.078588	0.07 (0.04-0.13)[c]	
	193-195	0.571363	0.12 (0.07-0.22)[d]	
	204	0.577998	0.12 (0.07-0.22)[d]	
	291-293	0.330585	0.10 (0.05-0.17)[c]	
	299-301	-0.800063	0.03 (0.01-0.08)[e]	
	304-305	-0.337555	0.05 (0.02-0.10)[e]	
	308-310	0.367514	0.10 (0.05-0.19)[c]	
	313	-1.30093	0.01 (0.01-0.06)[e]	
	377-379	0.273071	0.09 (0.04-0.18)[c]	
	391-392	0.198328	0.08 (0.05-0.15)[c]	
	432-434	1.21598	0.24 (0.13-0.46)[f]	
	444-446	-0.84677	0.03 (0.01-0.07)[e]	
	602-603	0.259465	0.09 (0.04-0.19)[c]	
	637-639	0.0691005	0.06 (0.03-0.12)[c]	
	689-690	0.116481	0.08 (0.04-0.16)[c]	
	811-812	0.551406	0.12 (0.06-0.23)[d]	
	865-866	-1.02955	0.02 (0.01-0.06)[e]	
	969-977	2.62002	1[g]	
Needed surgery		0.572577	1.77 (1.26-2.48)	<0.001

* Same letters indicate non-significant pairwise differences.
Source: Authors' data analyses.

The model presented an adequate fit (Hosmer-Lemeshow test for the 5-rank classification system: df=3; chi-square=2.73; p=0.435) and a fair discriminative performance (AUC=0.78) (Figure 1).

Validation of the predictive model, using the same coefficients, on the next year's sample (2017; N=7,096) also presented an adequate fit (Hosmer-Lemeshow test: df=3; chi-square=0.37; p>0.90), and the discriminative performance was again fair (AUC=0.76). (Figure 2)

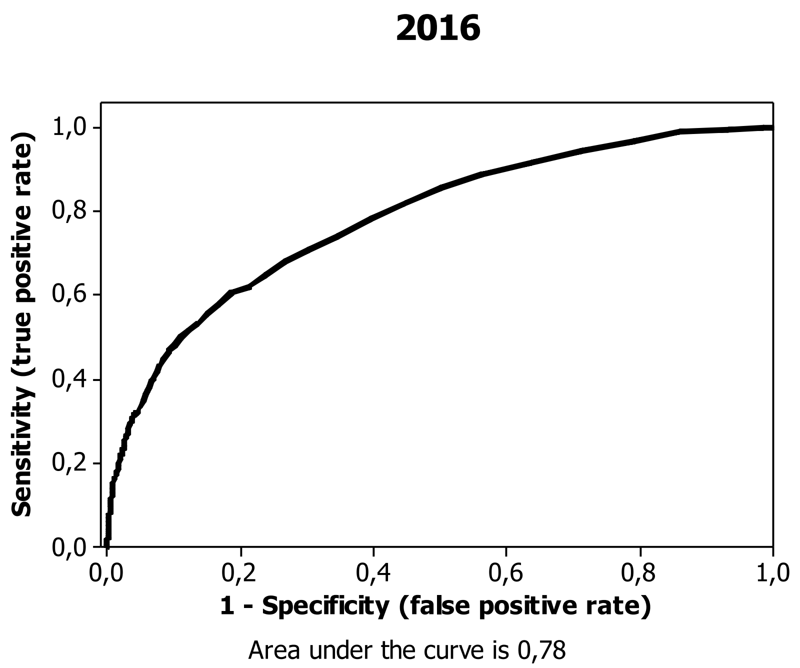
The resulting 5-rank classification system predicted a range of progressive death risks varying from 2.1% in the lower-risk category to 54.5% in the higher-risk. (Table 4)

Table 4 –Goodness of fit of a 5-rank classification system to predict the risk of in-hospital death in non-surgical admissions to general hospitals.

Risk classification	N	Observed deaths	Expected deaths	Observed discharges	Expected discharges	Median risk of death
0	3236	66	68	3170	3168	2.1%
1	1741	157	145	1584	1596	8.4%
2	1108	155	158	953	950	14.3%
3	643	190	158	453	485	24.5%
4	368	189	200	179	168	54.5%

Hosmer Lemeshow statistic = 0.3677; p>0.90. Predictive model based on index (2016) data, validated on the next year's (2017) admissions.
Source: Authors' data analyses.

Figure 1 – Receiver-operating characteristics curves (ROC) for the discriminative prediction model of in-hospital death, using index (2016) admission records of non-surgical admissions in general hospitals.



Source: Authors' data analyses.

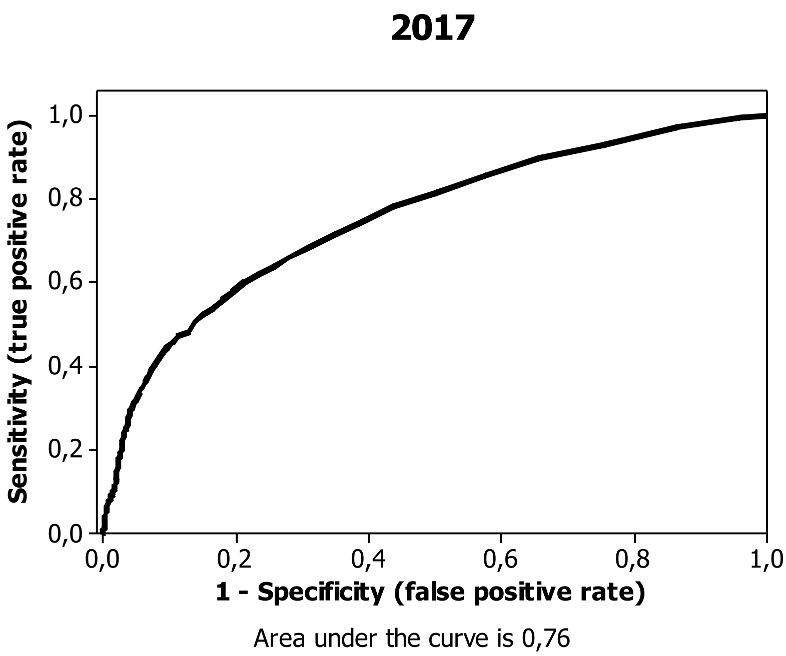
DISCUSSION

The main achievement of this study was to develop and validate a risk-classification system for death that is clinically useful for general hospital adult primarily non-surgical cases.

By performing risk classifications, clinical management decisions can be proposed in order to direct efforts aiming at risk mitigation. There are mortality risk classification systems aiming at specific diseases or conditions, for the critically ill (KNAUS et al., 1991) and for in-hospital pediatric mortality

(PARSHURAM, 2018). However, to our knowledge, no comprehensive risk classification system had yet been developed for the entire adult non-surgical case-mix of general hospitals.

Figure 2 – Receiver-operating characteristics curves (ROC) for the discriminative prediction model of in-hospital death, using next year's (2017) admission records of non-surgical admissions in general hospitals.



Source: Authors' data analyses.

One of the advantages of this risk classification system is that it can be automated, providing that electronic health records are available. Also, its output is dynamic, as new entries in the electronic records may instantly update a given patient's classification status.

The systematics of its modeling and calculations are flexible and may be replicated, by running specific regressions based on the target hospitals' clinical databases. Since the epidemiologic profile may change over time, models should be periodically updated on the same hospitals in order to verify its accuracy and fit. For example, when we ran an updated model on the 2017 and 2018 datasets of the same hospitals, the discriminant performance improved (AUC=0.82).

Admission to the ICU was one of the more relevant risk factors for death. This corroborates previous reports (GOMES et al., 2010; DIAS; MARTINS; NAVARRO, 2012], and naturally reflects case severity. Since the goal is to develop a risk classification system useful in all levels of hospital care, it is mandatory to assess whether the model predicts adequately when admission to the ICU does not occur. Sensitivity analyses were performed in order to analyze the predictive abilities and the fit of the model in two different ways: a) in the original index sample, by not including admission to the ICU in the model; or b) by running the statistics in a subsample that excluded ICU cases. In both cases, AUC remained in the 0.72-0.73 range and Hosmer-Lemeshow statistics presented adequate fits.

The population of clinical inpatients in this sample was mainly constituted of aged persons (mean 60 years-old). This reflects the epidemiology and burden of diseases in the region, where life-expectancy has increased and an epidemiologic transition is in progress [10]. Our results corroborate previous findings that age increases the risk of death (in this study, a 3% increment per year) in the context of hospital care (GOMES et al., 2010; MARTINS et al., 2011).

Male gender was also an independent significant risk factor (OR=1.21) for in-hospital death. This is in accordance with previous reports (GOMES et al., 2010; MARTINS et al., 2011) and may be a combination of biological and social predisposing conditions (ROGERS et al., 2010).

The diagnostic group more strongly predicting in-hospital death was 'HIV infections'. This probably reflects the relative severity of cases that were referred for hospital care, since Brazil has a distinguished and efficient public and universal program for the treatment of HIV infections and related conditions (GRECO; SIMÃO, 2013; DA FONSECA; BASTOS, 2018), so it is probable that cases that did result in admission were the most severe and/or associated with relevant comorbidity. Hepatic cirrhosis and lung infections were the other most relevant diagnostic risk factors. Admissions for hepatic cirrhosis generally occur in terminal stages of the disease (RAMACHANDRAN et al., 2018). Respiratory infections, however, are amongst the top reasons for hospital admissions in Brazil (GOMES et al., 2010), many times as complications of other major underlying disease (BAHLIS et al., 2018). Both cirrhosis and pneumonia usually present > 10% lethality rates among inpatient samples (BAHLIS et al., 2018; VERGARA et al., 2013).

Very short and prolonged lengths of stay were both risk factors for death among hospitalized patients. Early hospital deaths are probably related to acute and very severe cases: i.e. in this sample, stroke was one of the most prevalent diagnoses among the shorter stays (data not shown). On the other end, longer stays related deaths were possibly due to aggravation or complications of the original disease, including the need for an unplanned surgical intervention.

Limitations of this study include: a) analyses were limited to the available variables in the electronic patient records; b) regression results shall not be immediately be transported to other settings, unless validation strategies are previously performed; c) primary surgical admissions were not considered, but shall be addressed separately for the sake of prediction accuracy.

CONCLUSIONS

A dynamic risk classification system for in-hospital death, based on electronic records has been validated for non-surgical admissions of general hospitals. The 5-rank classification system showed adequate discriminative performance and fit, retaining those characteristics even when challenged with new data. The development of a similar classification system for primarily surgical admissions is warranted.

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