ORIGINAL ARTICLE

Model to predict risk for hospital admission and indicate the safety of reverse triage in a hospital emergency department: a prospective validation study

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Objectives. To prospectively validate a model to predict hospital admission of patients given a low-priority classification on emergency department triage and to indicate the safety of reverse triage.

Methods. Single-center observational study of a prospective cohort to validate a risk model incorporating demographic and emergency care process variables as well as vital signs. The cohort included emergency visits from patients over the age of 15 years with priority level classifications of IV and V according to the Andorran–Spanish triage system (Spanish acronym, MAT-SET) between October 2018 and June 2019. The area under the receiver operating characteristic curve (AUC) of the model was calculated to evaluate discrimination. Based on the model, we identified cut-off points to distinguish patients with low, intermediate, or high risk for hospital admission.

Results. A total of 2110 emergencies were included in the validation cohort; 109 patients (5.2%) were hospitalized. The median age was 43.5 years (interquartile range, 31-60.3 years); 55.5% were female. The AUC was 0.71 (95% CI, 0.64-0.75). The model identified 357 patients (16.9%) at low risk of hospitalization and 240 (11.4%) at high risk. A total of 15.8% of the high-risk patients and 2.8% of the low-risk patients were hospitalized.

Conclusions. The validated model is able to identify risk for hospitalization among patients classified as low priority on triage. Patients identified as having high risk of hospitalization could be offered preferential treatment within the same level of priority at triage, while those at low risk of admission could be referred to a more appropriate care level on reverse triage.

Keywords: Emergency department. Triage, low priority. Hospitalization.

Validación prospectiva de un modelo predictivo de ingreso y orientar la seguridad de la derivación inversa desde el triaje de los servicios de urgencias hospitalarios

Objetivo. Validar prospectivamente un modelo predictivo de ingreso hospitalario para los pacientes atendidos en el servicio de urgencias hospitalario (SUH) con baja prioridad de visita y determinar la capacidad predictiva del modelo para realizar con seguridad la derivación inversa.

Método. Estudio observacional unicéntrico de una cohorte prospectiva de validación de un modelo predictivo basado en variables demográficas, de proceso y las constantes vitales (modelo 3). Se incluyeron los episodios de pacientes > 15 años con prioridades IV y V MAT-SET atendidos entre octubre 2018 y junio 2019. Se evaluó la discriminación mediante el área bajo la curva de la característica operativa del receptor (ABC). Para determinar la capacidad de discriminación se crearon 3 categorías de riesgo: bajo, intermedio y alto.

Resultados. Se incluyeron 2.110 episodios, de los cuales 109 (5,2%) ingresaron. La mediana de edad fue de 43,5 años (RIC 31-60,3) con un 55,5% de mujeres. El ABC fue de 0,71 (IC 95%: 0,64-0,75). Según el modelo predictivo, 357 episodios (16,9%) puntuaron de bajo riesgo de ingreso y 240 (11,4%) de alto riesgo. El porcentaje de ingreso observado de los pacientes clasificados de alto riesgo fue de 15,8% mientras que el de los pacientes de bajo riego fue de 2,8%.

Conclusiones. El modelo predictivo validado permite estratificar el riesgo de ingreso de los pacientes con baja prioridad de visita. Los pacientes con alto riesgo de ingreso se les podría ofrecer una atención preferente dentro del mismo nivel de prioridad, mientras que los de bajo riesgo podrían ser redirigidos al recurso asistencial más adecuado (derivación inversa).

Palabras clave: Urgencias. Triaje. Ingreso. Bajo nivel de prioridad de visita.

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Introduction

For the organization of emergency departments (ED), both in terms of physical structure and human resources, is essential to carry out their duties effectively and efficiently.[1] Early identification of those patients who will require hospital admission and those in whom it is possible to perform reverse triage (RT) can allow the ED to better manage beds and avoid situations of collapse.[2]

Structured triage, performed by nurses upon arrival of the patient at the ED, aims to prioritize patient care according to their degree of urgency[3-5] and to optimize waiting time. Currently, 100% of publicly used EDs in the Catalan Health System (Spanish acronym, SISCAT) have a structured triage system (Andorran Triage Model version 4.5). In 2019 in Catalonia, 62.1% of hospital EDs did not present life-threatening or were not considered urgent care.[6] However, it is known that "what is urgent is not always serious and what is serious is not always urgent",[5,7,8] and here triage plays an important role in regulating the flow of incoming patients.

Between 70 and 80% of patients who consult the ED do so on their own initiative.[9,10] Once triage has been completed, the RT of patients from the ED to out-of-hospital emergency departments of not-so-urgent and non-urgent cases (priorities IV and V) that are not complex may be an essential measure to assign these patients to the most appropriate health care resource.[9,11-13] The advisory board of the Pla Nacional d'Urgències de Catalunya (PLANUC), in a document on urgent care in times of COVID,[14] urges that triage be used to assign RT to centers of lesser complexity. In addition, it recommends incorporating screening tools adapted to each care setting in triage and incorporating the systematic taking of vital signs in all patients.[14]

However, despite these recommendations, there are currently no validated decision-support tools in Spain to help professionals perform RT. International studies have shown that RT is a safe procedure that is accepted by most patients, with satisfaction rates of 76%.[15,16] RT reduces visits without increasing mortality[17] and therefore there is no increased risk to the health of individuals.[18] In addition, Bentley et al.[16] indicate that it may be more beneficial for the patient to be seen in the device that can best respond to his or her health problem.

On the other hand, one of the objectives of the ED should be to limit the length of stay of patients requiring admission to less than 24 hours.[14] The expected admission percentages for adult patient triage priorities I, II, III and IV-V range between 70-90%, 40-70%, 20-40% and 5-20% respectively.[19,20] The prediction of hospital admission is another key point in the organization of the ED. There are three studies in Spain on ED admission prediction models. The first of these is based on demographic variables, requests for complementary tests and prescription of drugs after the first medical evaluation of the patient.[21] The other two studies are retrospective and are based on information prior to medical assessment: one based on demographic and process variables collected routinely and available at the end of triage[22] and the other, developed by our group, focused exclusively on priorities IV and V and adding the vital signs.[23] The latter developed three predictive models, with equal specificity, but with greater sensitivity in model 3, which included the vital signs.[23] The aim of our study was to prospectively validate this predictive model for hospital admission of patients seen in the ED with low visit priority according to the triage system, and to determine the predictive capacity of the model to safely perform the RT of these patients.

Methods

Prospective observational cohort study of temporal validation conducted in the ED of a Catalan public hospital between October 10, 2018 and June 22, 2019. The center provides health coverage to 258 000 inhabitants and the ED attended 113 512 emergencies in 2018, of which 68% were priorities IV and V. The study was approved by the reference clinical research ethics committee (Spanish acronym, CEI 18/63). Participation was voluntary and informed consent was obtained from patients.

Patients over 15 years of age classified as priorities IV and V according to the Andorran Triage Model/Spanish Triage System (Spanish acronym, MAT-SET) who were consecutively seen in the ED during the study period were included. Patients in whom triage could not be performed or who did not give consent to participate were excluded. The program used for triage was Web Epat version 4.5 (MAT/SET). Triage was performed by 2 nurses from 7:30 am to 11:30 pm and by a nurse from 11:30 pm to 7:30 am. The nurses who performed the triage had at least 2 years of experience in the emergency department and had completed a specific 1-month course.

Demographic variables (age and sex, country of origin) and process variables (day and time of the urgent care request, origin, means of transport of arrival, consultation during the 72 hours prior to the ED of our center were collected, whether or not they were related to the index episode and the destination of the patient at discharge). In addition, vital signs taken at triage or prior to medical consultation were recorded. Vital signs were categorized: systolic blood pressure (SBP) < 90 mmHg, 90-149 mmHg and ≥ 150 mmHg; and diastolic blood pressure (DBP) < 60 mmHg, axillary temperature > 37ºC, heart rate (HR) > 100 beats/min (bpm), respiratory rate (RF) > 24 breaths/minute (brpm) and baseline arterial oxygen saturation (SpO_2) < 93%, 93-95% and > 95%. The main dependent variable was hospital admission. Hospitalization in the center itself and in home hospitalization or with transfer to another hospital, social-health center or mental health center were regarded as such.

The sample size for the validation study was calculated according to the maximum modeling principle. To this end, it was established that at least 10 events (hospital admissions) were available for each of the explanatory variables of the different referral models.

Considering that the maximum predictive model to be validated contained 11 explanatory variables (triage level, sex, age, origin, means of arrival at the ED, previous ED consultation 72 hours, SBP, DBP, axillary temperature, HR and SpO_2), it was necessary to include 110 ED episodes whose discharge destination was admission. Assuming an admission rate of 6.4%,[23] 1719 ED episodes with priority IV and V had to be included.

Quantitative variables are presented with median and interquartile range (IQR) and qualitative variables are shown in absolute values and relative frequencies.

The normality of continuous variables was assessed with the Kolmogorov-Smirnov test. Models 1 and 3 previously developed retrospectively by Leey-Echavarría et al.[23] were validated.

Multivariable models based on generalized estimating equations (GEE) with an exchangeable correlation matrix structure[23] were used to develop predictive models of hospital admission. For the development samples, all episodes of patients older than 15 years classified as priority levels IV and V according to MAT-SET in the ED between January 1 and December 31, 2015 were included.

In model 1, all ED episodes with valid values for demographic and process variables were included (n = 53 860). Model 3 (n = 10 412) included emergency episodes with valid values for demographic and process variables and vital signs (SBP, DBP, axillary temperature, HR and SpO_2). For each of the predictive models, the beta coefficients of each of the independent variables were used to calculate the admission prediction score (Table 1).

In the prospective study, according to the discriminatory capacity of model 3, 3 risk categories were created: low, intermediate, and high risk. The cut-off point for the high entry risk category was set at that value at which specificity was maximized to minimize the number of false positives. The cut-off point for the low entry risk category was set at that value at which sensitivity was maximized to minimize the number of false negatives.

For both the development and validation models, the discrimination capacity of each model was evaluated using the area under the curve (AUC) from the receiver operating characteristic (ROC) together with its 95% CI. To assess the degree of agreement between the probabilities predicted by the models and those observed, calibration curves[24] were used together with the calibration-in-the-large and calibration slope parameters obtained using STATA pmcalplot command.[25]

For each cut-off point, diagnostic validity parameters were estimated: sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) together with 95% CI. A bilateral statistical significance level of 5% ($P < .05$) was used. IBM SPSS Statistics v.26 (IBM Corporation, Armonk, New York, United States) and STATA v.14 (StataCorp LP, College Station, Texas, United States) were used for statistical analysis.

Table 1. Coefficients β used for the calculation of the scores for each of the models obtained in the development study (retrospective study)[23]

	Development sample Model 1 (N = 53860) Coef. Beta (α)	Development sample Model 3 (N = 10412) Coef. Beta (β)
Triage level (IV)	0.122	–0.093
Gender (Male)	0.339	0.378
Age (years)		
45 to 64	0.758	0.908
65 to 74	1.177	1.262
75 to 84	1.643	1.666
> 84	1.915	1.906
Origin		
Primary care resource	0.689	0.663
Social-health network resource	0.800	0.843
General acute care hospital	2.381	2.418
Mean time to arrival in the emergency department (TSC/SEM)	1.568	1.316
Prior emergency consultation (72 hours) (Yes)	0.843	0.764
SBP (mmHg)	–	
< 90	–	–1.577
≥ 150	–	–0.186
DBP (< 60 mmHg)	–	0.451
Axillary temperature (> 37°C)	–	0.829
HR (> 100 beats/min)		0.503
Basal SpO_2		
93-95%		0.531
< 93%		0.980
Intercept (β_0)	–4.547	–4.034

For each of the models, the calculation of the total score is obtained from the sum of the beta coefficients corresponding to the combination of independent variables presented by the patient: Model 1 score = 0.122 x triage level IV + 0.339 x male gender + 0.758 x age 45 to 44 years + 1177 x age 65 to 74 + 1643 x age 74 to 85 years + 1915 age > 84 years + 0.689 x origin primary care resource + 0.800 x origin of resource from the social-health network + 2381 x origin general acute hospital + 1.568 x means of arrival at the emergency department by ambulance (TSC or SEM) + 0.843 x previous ED consultation (72 hours). Model score 3 = -0.093 x triage level IV + 0.378 x sex male + 0.908 x age 45 to 44 years + 1.262 x age 65 to 74 + 1.666 x age 74 to 85 years + 1.906 age > 84 years + 0.663 x origin primary care resource + 0.843 x origin social-health network resource + 2.418 x origin general acute hospital + 1.316 x means of arrival to the ED by ambulance (TSC or EMS) + 0.764 x previous ED consultation (72 hours) -1.577 x SBP < 90 mmHg -0.186 x SBP ≥150 mmHg + 0.451 x DBP < 60 mmHg + 0.829 x axillary T > 37°C + 0.503 x HR > 100 + 0.531 x SpO_2 93-95% + 0.980 x SpO_2 < 93%. Probability of admission according to model 1 = 1/{1 + exp [- (-4.547 + model score 1)]}.
Probability of admission according to model 3 = 1/{1 + exp [- (-4034 + punctation model 3)]}.
EMS: emergency medical system. Does not include the patient referred from one device to another in which the EMS intervenes to make the transfer; SBP: systolic blood pressure; DBP: diastolic blood pressure; HR: heart rate; SpO_2.

Results

During the study period, 7699 emergency episodes were attended. Of these, 2479 emergency episodes with low priority were included; 369 (14.9%) episodes were excluded from the statistical analysis because of missing values in the vital signs. Of the 2110 episodes in the validation sample, 96.8% were priority IV and 3.2% were priority V (Figure 1).

The characteristics of the patients included in the development and validation samples are shown in Table 2. In the validation sample, the median age was 43.5 years (interquartile range: 31-60.3) with 55.5% of the patients being female. Some 19.8% of the patients seen were ≥ 65 years old. The highest number of visits was in the afternoon (62.3%), 91.5% of them came on their own initiative. A total of 96.8% came by their own means and 2.4% of the episodes had a previous visit to the emergency department within the last 72 hours. One hundred and nine episodes (5.2%) required hospital admission (5.2% and 2.9% of priority IV and V, respectively). The diagnostic validity parameters (sensitivity, specificity, PPV and NPV) of the development (retrospective study) and validation (prospective study) samples for the prioritization of patients with an increased risk of admission before the medical visit are shown in Table 3. For model 1, an AUC of 0.79 (95% CI: 0.78-0.80) and 0.70 (95% CI: 0.62-0.73) were obtained for the development and validation samples, respectively. For model 3, an AUC of 0.82 (95% CI: 0.80-0.83) and 0.71 (95% CI: 0.64-0.75) was obtained for the development and validation samples, respectively. The calibration obtained in the derivation models was lower than that of the development models. For model 1, an intercept of -1.297 and a slope of 0.636 was obtained and for model 3, the intercept was -1.651 and the slope was 0.791, indicative of an overestimation of risk by the models.

In the development sample, the cut-off point of the model 3 score was set at 3.1 to obtain a specificity of 95%. In the development sample we obtained a sensitivity of 39.7% and a specificity of 95.1% while in the validation sample the sensitivity was 14.7% and the NPV 95.5%. To improve sensitivity, we established a new cut-off point for the score at 1.9. For this cut-off point we obtained a sensitivity of 67.6% and a specific-

Table 2. Characteristics of ED episodes included in the development (retrospective study[23]) and validation (prospective study) samples

	Development sample Model 1 N = 53 860 n (%)	Development sample Model 3 N = 10 412 n (%)	Validation sample N = 2110 n (%)
Triage level			
V	2723 (5.1)	139 (1.3)	68 (3.2)
IV	51 137 (94.9)	10 273 (98.7)	2042 (96.8)
Age (years) (median [IQR])	44.5 [31.1-63.9]	49.0 [33.6-70.3]	43.5 [31.0-60.3]
15 to 44	27 392 (50.9)	4633 (44.5)	1112 (52.7)
45 to 64	13 660 (25.4)	2529 (24.3)	579 (27.4)
65 to 74	5171(9.6)	1141 (11.0)	205 (9.7)
75 to 84	5062 (9.4)	1265 (12.1)	156 (7.4)
> 84	2575 (4.8)	844 (8.1)	58 (2.7)
Gender			
Female	29 125 (54.1)	5825 (55.9)	1172 (55.5)
Male	24 735 (45.9)	4587 (44.1)	938 (44.5)
Country of origin			
Spain	7574 (17.7)	1450 (17.9)	10 (0.5)
Other	35 177 (82.3)	6645 (82.1)	2098 (99.5)
Time slot			
14:01-22:00	24 451 (45.4)	4931 (47.4)	1314 (62.3)
22:01-07:00	7191 (13.4)	1550 (14.9)	204 (9.7)
07:01-14:00	22 218(41.3)	3931 (37.8)	5928 (28.1)
Day of the week			
Sunday	7588 (14.1)	1528 (14.7)	314 (14.9)
Monday	8747 (16.2)	1628 (15.6)	313 (14.8)
Tuesday	7845 (14.6)	1433 (13.8)	218 (10.3)
Wednesday	7661 (14.2)	1524 (14.6)	258 (12.2)
Thursday	7425 (13.8)	1493 (14.3)	369 (17.5)
Friday	7375 (13.7)	1385 (13.3)	337 (16.0)
Saturday	7219 (13.4)	1421 (13.6)	301 (14.3)
Part of the week			
Weekdays (Monday to Friday)	39 053 (72.5)	7463 (71.7)	1495 (70.9)
Weekends	14 807 (27.5)	2949 (28.3)	615 (29.1)
Origin[1]			
Home	48 879 (90.8)	9167 (88.0)	1934 (91.7)
Primary care resource	4731 (8.8)	1199 (11.5)	168 (8.0)
Social-health network resource	66 (0.1)	15 (0.1)	3 (0.1)
General acute care hospital	184 (0.3)	31 (0.3)	5 (0.2)
Coming from another emergency department			
No	49 059 (99.6)	9189 (99.6)	2104 (99.7)
ED	183 (0.4)	30 (0.3)	6 (0.3)
EMS	22 (0.04)	5 (0.1)	-
Means of arrival at the emergency department			
By their own means	49 524 (91.9)	9090 (87.3)	2043 (96.8)
By ambulance (TSC or SEM)	4336 (8.1)	1322 (12.7)	67 (3.2)

(Continues)

Table 2. Characteristics of ED episodes included in the development (retrospective study[23]) and validation (prospective study) samples (Continuation)

	Development sample Model 1 N = 53 860 n (%)	Development sample Model 3 N = 10 412 n (%)	Validation sample N = 2110 n (%)
Prior emergency consultation (72 hours)			
No	51 736 (96.1)	1006 (96.1)	2060 (97.6)
Yes	2124 (3.9)	406 (3.9)	50 (2.4)
SBP (mmHg) [median (IQR)]	130 [117-145]	130 [117-145]	133 [120-145]
< 90	50 (0.2)	23 (0.2)	4 (0.2)
90-149	17 334 (79.9)	8423 (80.9)	1731 (82.0)
≥ 150	4315 (19.9)	1966 (18.9)	375 (17.8)
DBP (mmHg) [median (IQR)]	76 [69-84]	76 [69-84]	77 [69-86]
≥ 60	20 085 (92.9)	9671 (98.9)	1946 (92.2)
< 60	1536 (7.2)	741 (7.1)	164 (7.8)
Axillary Temperature (°C) [median (IQR)]	36.3 [36.0-36.7]	36.3 [36.0-36.7]	36 [36-36]
≤ 37	14 641 (88.3)	9136 (87.7)	1959 (92.8)
> 37	1942 (11.7	1276 (12.3)	151 (7.2)
HR (beats/min) [median (HR)]	82 [72-93]	82 [72-93]	83 [72-96]
≤ 100	19 567 (86.8)	8796 (84.5)	1768 (83.8)
>100	2985 (13.2)	1616 (15.5)	342 (16.2)
RR (brpm) [median (IQR)]	16 [14-20]	20 [16-20]	14 [12-14]
≤ 24	2103 (96.4)	1201 (95.2)	2107 (99.9)
> 24	78 (3.6)	60 (4.8)	3 (0.1)
Basal SpO_2 (%) [median (IQR)]	99 [97-100]	99 [97-100]	100 [99-100]
> 95	15 024 (90.5)	9387 (90.2)	2070 (98.1)
93-95	1316 (7.9)	851 (8.2)	36 (1.7)
< 93	265 (1.6)	174 (1.7)	4 (0.2)

[1]Origin: (1) Home, social residence, educational center, workplace, public road; (2) Primary care resource (public or private), outpatient clinic of the same hospital; (3) Resource of the social-health network; (4) General acute hospital or psychiatric monographic hospital, home hospitalization.
ED: emergency department; EMS: Medical Emergency System (does not include patients referred from one device to another in which the EMS intervenes for transfer); SBP: systolic blood pressure; DBP: diastolic blood pressure; HR: heart rate; bpm: breaths per minute; SpO_2: arterial O_2 saturation; IQR: interquartile range; RR: respiratory rate.

ity of 81.7% in the development sample, while the sensitivity was 34.9% and the specificity 89.9% for the validation sample.

The diagnostic validity parameters of the development and validation samples for the RT of patients with a low probability of hospital admission are shown in Table 4. The cut-off point for the model 3 score was set at -0.093 in the development sample. In the development sample, a sensitivity of 97.7% and NPV of 97.9 were obtained. In the validation sample, the sensitivity was 90.8% and the NPV was 97.2%.

The distribution of patients according to risk stratification based on the model 3 score is shown in Figure 2. 11.4% of the EDs scored high risk for admission and 16.9% low risk. The observed percentage of admission of patients classified as high risk was 15.8%, while that of low-risk patients was 2.8%.

Discussion

The present study has allowed us to prospectively validate a predictive model for hospital admission of patients seen in an ED with low visit priority. Model 3 is based on 11 demographic and process variables and on the vital signs that can be obtained during triage. This model has an acceptable predictive capacity and allows patients to be classified into three admission risk groups. Those at low risk would be candidates for RT, while those at high risk could be offered differential care within the same visit priority.

Most of the predictive models in the literature have been developed based on different triage models/scales together with administrative or clinical variables[22,26,27] to predict admission for any ED priority.[22,26-28] The risk of admission of EDs with priorities I-II-III is much higher than that of IV-V, which possibly explains the better diagnostic performance of these models with AUCs above 0.8. Parker et al.[28] recommend using objective variables, such as the inclusion of vital signs, to favor model replicability.

Most studies[22,26-28] focus on admission prediction, but do not analyze the possibility of RT as another ED management tool. Gilbert et al.[29] perform RT safely using tools based on triage scales (PERSEE algorithm) to improve management and decrease ED workload.

On the other hand, there is no study performed with the structured MAT-SET based triage system for admission prediction. This fact, together with the low triage priority level of the patients in this study makes comparison with other predictive models difficult.

In our study, 5.2% of patients with priority IV-V were admitted to hospital. This percentage is similar to that of other published studies[1,30] which, moreover, suggest that patients who present on their own initiative present less urgent processes. Of the characteristics

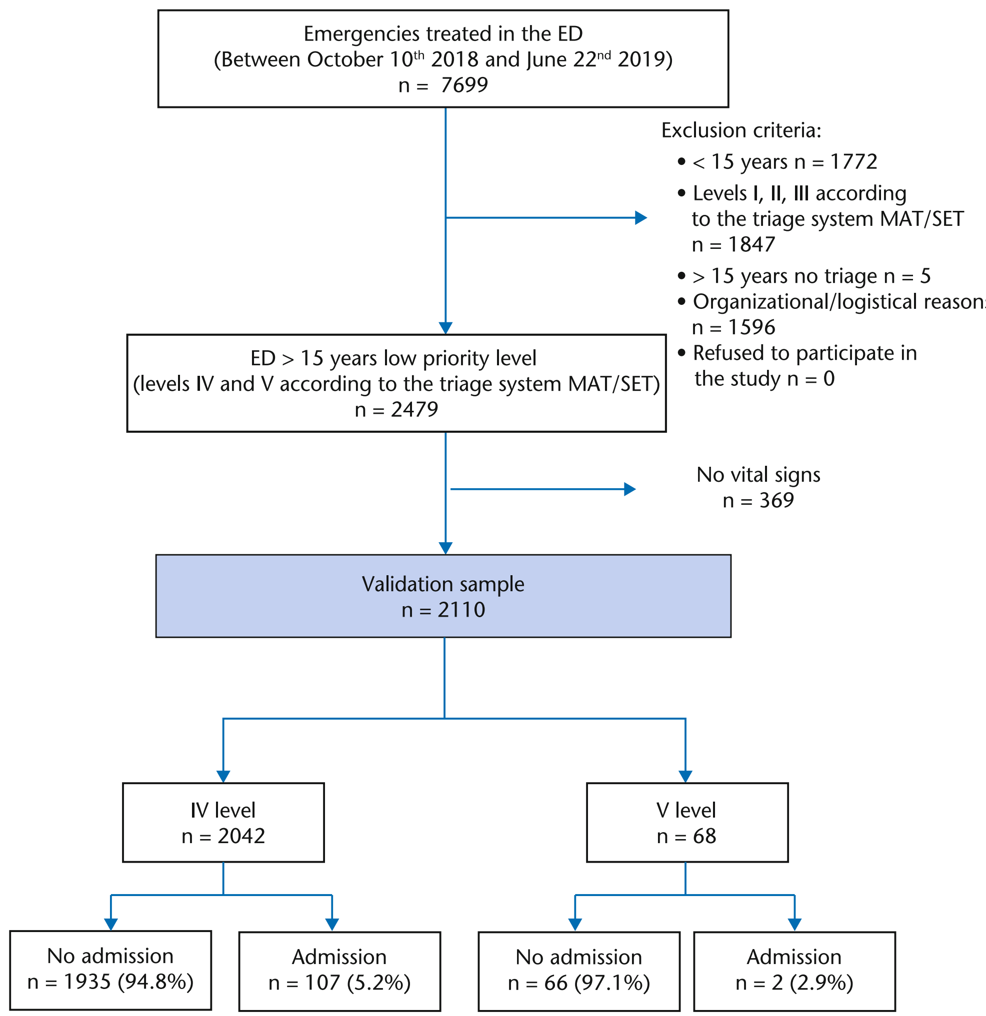

Figure 1. Patient flow diagram.
ED: emergency department. Spanish acronym, MAT/SET: Model Andorrà de Triatge/Spanish Triage System.

of the patients included in the validation sample, it should be noted that 80.1% were under 65 years of age, 95.1% attended on their own initiative and 62.3% in the afternoon.

These results are congruent with previous studies carried out in Spain, where the mostly young user goes to the ED because of the permanent 24-hour accessibility,[31] greater confidence in the hospital specialists,[32] less accessibility in primary care[33] and the expectation of having faster care or not knowing of the existence of another level of care.[34]

The inadequate use of EDs by young patients and those with less severe conditions reinforces the need for patient flow redirection circuits such as RT.[35]

In RT, users, after being assessed by the triage nurse, are redirected to another level of care where they will be evaluated by other health professionals, maintaining continuity of care. Salmeron et al.[9] investigated the effectiveness and safety of RT from triage and concluded that referral by an accredited nurse using the Triage Assistance program without a medical visit is safe and effective. Our predictive model would allow RT to be performed safely, with only a 2.8% false negative rate. This percentage means that 10 patients who scored in the low-risk category ended up being admitted. All of them were young women, with a mean age of 34.8 years, and none of them were life-threatening at discharge. The main reason for consultation in these 10 patients was abdominal pain and in one patient the final diagnosis was appendicitis. Pain is a frequent symptom, but at the same time very unspecific in the face of RT. Therefore, when the reason for consultation is "abdominal pain", it could be considered not to perform RT.

This study has two strengths. The first is that it is the only study that prospectively validates a model for predicting hospital admission of patients with MAT/SET priorities IV-V, who account for 65% of visits.[1] The second strength is that this predictive model allows simultaneous RT and prioritization of patients at high risk of admission.

The study has several limitations. The first is that 20.7% of the patients in the study were not evaluated

Table 3. Predictive models for hospital admission. Diagnostic validity parameters of the development (retrospective study[23]) and validation (prospective study) samples for the prioritization of patients with a higher probability of admission before the medical visit

	Diagnostic validity parameters					
	Developmental sample Model 1 (n = 53 860)	Validation sample Model 1 (n = 2110)	Developmental sample Model 3 (n = 10 412)		Validation sample Model 3 (n = 2110)	
AUC ROC (95% CI)	0.79 (0.78-0.80)	0.70 (0.62-0.73)	0.82 (0.80-0.83)		0.71 (0.64-0.75)	
Cut-off point	2.8	2.8	3.1	1.9	3.1	1.9
Sensitivity (95% CI)	36.5 (34.9-38.2)	17.4 (10.8-25.9)	39.7 (37.1-42.3)	67.6 (65.0-70.0)	14.7 (8.6-22.7)	34.9 (26.0-44.6)
Specificity (95% CI)	95.4 (95.2-95.6)	98.0 (97.2-98.5)	95.1 (94.7-95.6)	81.7 (80.9-82.5)	98.7 (98.1-99.1)	89.9 (88.5-91.2)
Positive predictive value (95% CI)	35.1 (33.6-36.7)	31.7 (20.3-45.0)	55.8 (52.6-58.9)	36.4 (34.5-38.3)	38.1 (23.6-54.4)	15.8 (11.5-21.1)
Negative predictive value (95% CI)	95.7 (95.5-95.8)	95.6 (94.6-96.5)	91.1 (90.5-91.6)	94.2 (93.7-94.7)	95.5 (94.5-96.4)	96.2 (95.2-97.0)

ROC: Receiver operating characteristics.

for eligibility due to organizational reasons. The high pressure on triage care at certain times, which requires compliance with triage quality standards (10 minutes),[20] was the reason why this percentage of patients could not be evaluated. However, we consider that there was no selection bias given that no patients could be included in these peaks of care activity, and therefore we believe that the study would be reproducible in any ED. We believe that in future studies the triage response time should be considered as an exclusion criterion.

The second limitation is that this model has a reduced capacity for income discrimination with respect to the development study. One of the reasons for this would be the very likely overfitting of the developmental models. The algorithms obtained in the development samples would be considering as valid only data identical to those in the training data sets. In this sense, despite being a temporal validation, same center and same patients, the patients in the validation sample would be more similar to the patients in the development sample of model 1 (n = 53 860) than to those in model 3 (n = 10 412).

The predictive model containing the vital signs was the one with the greatest discriminatory capacity. However, one of the limitations of the development sample was that only 19.3% of the emergencies attended had all the vital signs recorded in the clinical history. In the development sample of model 1, 6.4% of the patients required hospital admission (6.4% and 4.9% of priority IV and V, respectively) while in the development sample of model 3, the admission rate was 13.4% (13.5% and 9.45 for priority IV and V, respectively).

In the referral sample, 5.2% of patients required hospital admission (5.2% and 2.9% of priority IV and V, respectively). This decrease in discrimination could be explained by a lower severity of patients in the validation sample. Nevertheless, in order to maintain the sensitivity obtained in the development study, we lowered the cut-off point initially planned for admission prioritization. The third limitation is that this is a prediction model validated in a single care center. Finally, the last limitation refers to the reproducibility of the model conditioned by the triage system in the ED. The MAT-SET is present in 37.3% of EDs in Spain[36] and in 100% in Catalonia.

The practical applicability of this model is relevant, as it can help to improve the appropriateness of the care process at both patient entry and destination. The identification of high-risk patients does not imply the performance of additional diagnostic tests, but simply a reduction in ED waiting time. The recommended wait times for priority IV and V EDs according to MAT-SET are 45 and 60 minutes, respectively. A false positive (patient at risk according to the score who will not be admitted) will not have any adverse events.

And, on the other hand, a false negative should remain in the ED waiting room for the time that would correspond to the usual practice of the center. The scale can also be a good tool for decongesting a good tool for decongesting the ED by identifying those patients at very low risk of admission for whom it is possible to perform RT from triage to RT. In this case, a false negative may result in a reconsultation to the ED in less than 72 hours.

Tabla 4. Predictive models for hospital admission. Diagnostic validity parameters of the development (retrospective study23) and validation (prospective study) samples for the derivation of patients with a higher probability of admission before the medical visit

	Diagnostic validity parameters			
	Developmental sample Model 1 (n = 53 860)	Validation sample Model 1 (n = 2110)	Developmental sample Model 3 (n = 10 412)	Validation sample Model 3 (n = 2110)
AUC ROC (95% CI)	0.79 (0.78-0.80)	0.70 (0.62-0.73)	0.82 (0.80-0.83)	0.71 (0.64-0.75)
Cut-off point	0.122	0.122	–0.093	–0.093
Sensitivity (95% CI)	93.8 (93.0-94.6)	86.2 (78.3-92.1)	97.7 (96.8-98.4)	90.8 (83.8-95.5)
Specificity (95% CI)	24.4 (24.3-25.0)	28.0 (26.1-30.1)	16.7 (15.9-17.5)	17.3 (15.7-19.1)
Positive predictive value (95% CI)	7.8 (7.5-8.1)	6.1 (5.0-7.4)	15.4 (14.6-16.1)	5.6 (4.6-6.8)
Negative predictive value (95% CI)	98.3 (98.1-98.5)	97.4 (95.7-98.5)	97.9 (97.1-98.6)	97.2 (94.9-98.6)

ROC: Receiver operating characteristics.

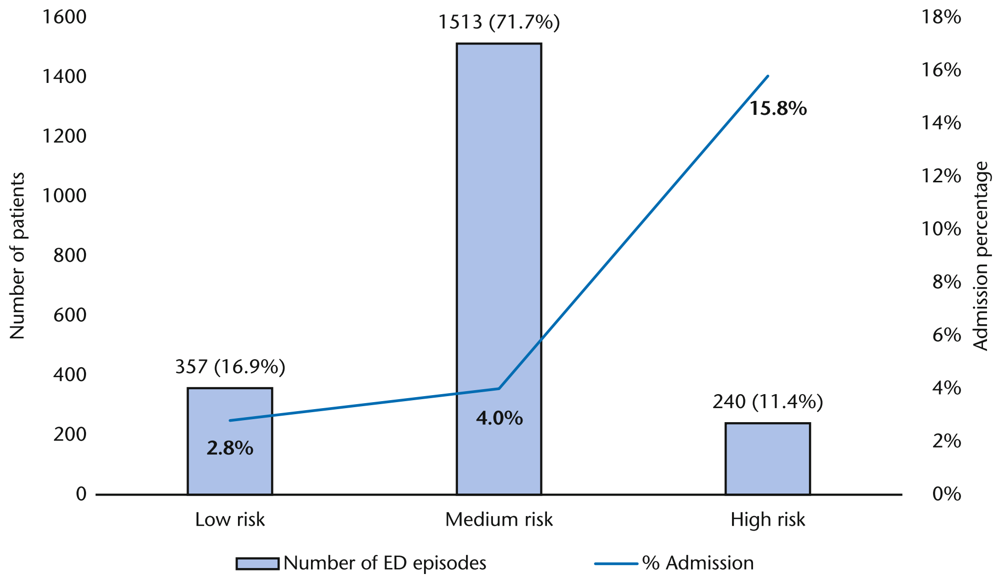

Figure 2. Distribution of patients according to risk stratification based on model 3 and percentage of hospital admissions observed.

In a hospital with the characteristics of the one studied, which attends around 113 000 emergencies per year, of which 68% are priorities IV and V, with the help of this predictive model 61 patients could be identified each day (25 admission prediction patients -9100 patients per year- and 36 RT patients -13 100 patients per year-) representing 29% of the total number of low priority patients per day. We believe that this model could complement and improve the current MAT/SET in low visit priority patients by creating an integrated application in triage to determine admission risk in IV-V priority patients. The results obtained open a new line of research to evaluate external validity in a multicenter study. However, if the performance obtained in an external validation is similar to that obtained in our validation sample, it might be advisable to consider recalibrating the model or even re-estimating the model by reducing the number of covariates or including new predictors according to the results obtained.

In conclusion, we believe that it is possible to have a predictive model from triage, before the medical visit, that allows prioritization and redirection of the flow of low-priority patients attending the ED. This model would facilitate decision-making at triage, improve resource management and reduce waiting times.

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