Journal of Health Research
eISSN 2586-940X

Volume 39 | Issue 3 Article 7

2025

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ORIGINAL STUDY

Predicting Hospitalisation in Older Patients Attended in the Emergency Department Using Classical and Artificial Intelligence Mathematical Strategies

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Abstract

Background: **The ageing population poses a significant challenge for health and social care systems. Emergency Departments (EDs) frequently experience overcrowding due to the high volume of patients and the limited availability of hospital beds. From the perspective of bed management planners, knowing the likelihood of a patient's admission at the**

Received 14 October 2024; revised 18 January 2025; accepted 19 January 2025.
Available online 14 June 2025

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https://doi.org/10.56808/2586-940X.1141

earliest stage of care can be highly beneficial for effective resource planning. The goal of our study was to develop a prediction model to identify patients with a high probability of being admitted to the hospital.

Methods: **We included all patients aged 65 or older who were treated over the course of one week in 52 Spanish Emergency Departments. The data collected included socio-demographic characteristics, baseline functional status, comorbidities, vital signs, chronic treatments, and laboratory test results. The primary outcome variable was hospital admission. We applied several mathematical strategies to develop the most accurate model for identifying high-risk patients likely to require hospitalisation.**

Results: **The most effective model was developed using a random forest algorithm, incorporating various variables available during patient care in the ED. The probability of admission was categorised into four risk groups: 2.19 %, 15.65 %, 25.09 %, and 57.08 %. The resulting model had a sensitivity of 0.88.**

Conclusion: **We developed a high-sensitivity score for hospital admission in older patients treated in the ED to enhance the management of patient flow by bed planners. This score will help prevent ED overcrowding, which compromises patient safety and disrupts the healthcare system.**

Keywords: Emergency medicine, Health care system, Hospital prediction, Overcrowd

1. Introduction

The global population is ageing, presenting significant challenges for health and social care systems worldwide [1,2]. In Europe, the number of people aged 65 or older is expected to increase from 90 million in 2019 to 130 million by 2050 [3].

Older patients are associated with a higher consumption of hospital resources, such as more diagnostic tests, consultations with specialists, longer stays in the Emergency Department (ED), and greater use of hospital bed resources [4,5]. They also experience worse health outcomes, including higher mortality rates, frequent ED visits, functional deterioration, and increased institutionalization [6,7]. For instance, hospital admission rates significantly rise with age, reaching 50 % in individuals over 80 years old [8]. As a result, this age group heavily influences patient flow in the ED and overall hospital activity. Moreover, older patients are more likely to present with cognitive, functional, and social deficits, which necessitates special considerations in emergency care. Studies have shown that EDs adapted to receiving older patients can reduce hospital admissions [9]. This not only lowers costs but also prevents complications associated with prolonged hospitalisation.

The ED is a high-pressure environment due to the large number of patients seen simultaneously and the limited availability of physicians [10]. Overcrowding has a negative impact on both patient health and the functioning of the healthcare system [11,12]. Strategies to reduce ED overcrowding generally fall into five categories: improving organisational workflow, increasing investment in primary care, creating new dedicated professional roles, implementing structural and labour changes, and developing predictive simulation models using mathematical algorithms [13].

ED arrivals follow predictable diurnal and seasonal patterns, with peak times in the morning and early evening. However, hospital discharges typically occur later in the day, creating bottlenecks in patient flow [14]. This mismatch between ED patient flow and hospital discharge times leads to patients "boarding" in the ED or being admitted to inappropriate wards. These inefficiencies contribute to longer hospital stays [15], increased risk of medical errors [16], and poorer long-term outcomes, particularly for older patients [17].

From the perspective of bed management planners, predicting the likelihood of a patient's admission at the earliest point of contact in the ED would be highly beneficial. Accurate predictions allow for better resource allocation, by anticipating bed needs hours in advance. A predictive model with sufficient accuracy can help identify clinical patterns and potential risk situations in real-time, ultimately improving the quality of care in the ED. By forecasting the number of admissions, hospital administrators can optimize resource management [18]. Early identification of high-risk patients is crucial for improving outcomes and reducing the strain on healthcare systems.

In light of these challenges, the primary objective of our study was to develop a predictive admission model of hospitalisation for patients aged 65 years and older seen in the ED. We aimed to use only variables available during the ED visit by the patient and employed various Machine Learning (ML) models to identify the most accurate and sensitive model.

2. Methods

2.1. Description of the EDEN challenge

The EDEN challenge originated from the SIESTA network [19], encompassing 52 Spanish EDs, representing approximately 20 % of public healthcare EDs in Spain. The results of this challenge have recently been presented [20]. The EDEN (Emergency Department Elderly Needs) challenge was a research initiative aimed at identifying elderly patients in the emergency department who would benefit from a different approach to care. The study's purpose was to develop and validate a predictive model to select older patients at high risk of adverse outcomes, with the goal of improving their management and outcomes in the emergency setting. The inclusion period was of seven days, from April 1 to April 7, 2019. There were no exclusion criteria, and EDs that opted to participate were required to include all patients treated in the ED during the study period.

2.2. Study design

Six socio-demographic characteristics were analysed, including alcohol and tobacco use, five factors related to the patient's baseline functional status, vital signs, chronic treatments, and the results of the first blood test requested. The primary outcome variable was hospital admission.

2.3. Statistical analysis

A descriptive analysis of the entire sample was performed, presenting frequencies and percentages for categorical variables, and means with standard deviations or medians with 1st and 3rd quartiles for continuous variables. The characteristics of hospitalised and discharged patients were compared using the Chi-square test for categorical variables and the non-parametric Wilcoxon test for continuous variables.

The dataset was divided into three homogeneous subsets: 70 % for the training set, 10 % for validation (the combined training and validation sets form the derivation sample), and 20 % for the test set. A descriptive analysis was performed to verify the homogeneity of these subsets by comparing categorical variables using the Chi-square test and continuous variables using the Wilcoxon test.

Predictions of hospitalisation were made using several ML models, including Random Forest (RF), Decision Tree (DT), KNN (K-Nearest Neighbors), SVM (Support Vector Machine), Logistic Regression, and the boosting techniques Gradient Boosting Classifier (GBC) and XGBoost. The hyperparameters for these classification methods were optimized through a random hyperparameter search, aimed at maximizing sensitivity.

Two models for evaluating admission risk were developed: one incorporating variables obtained from blood tests (Model 1) and another based solely on clinical variables, excluding blood test results (Model 2).

The validation of the models was conducted in both the derivation and test sets, using metrics such as sensitivity, accuracy, precision, and area under the curve (AUC) [21]. Receiver operating characteristic (ROC) curves were also generated for both data subsets. Model calibration was examined through calibration curves, which assess the agreement between observed and predicted event rates across subgroups, such as deciles of predicted risk.

The optimal model was selected through bootstrapping, generating 1000 different datasets and analysing whether there were significant differences between model evaluation metrics using a 95 % confidence interval (CI).

Based on the distribution of predicted probabilities for the outcome, four risk groups were created. Optimal thresholds for predictive probabilities were determined using the "catpedri" function from the R package CatPedri [22]. The performance of the risk classification was evaluated by comparing hospitalisation rates between categories and calculating AUC values for both the derivation and test samples. Finally, sensitivity and specificity were calculated for each cut-off point [23].

The contribution of each feature to the prediction of hospitalisation in the best-performing model, based on the aforementioned evaluation metrics, was assessed using the SHapley Additive exPlanations (SHAP) method [24]. SHAP values quantify the impact of including a feature on the model's output by considering all possible feature combinations. Features marked in blue indicate values less likely to predict hospitalisation, while those in red represent values more likely to predict the outcome.

2.4. Ethics statement

The EDEN project was approved by the Clinical Research Ethics Committee of the Hospital Clínico San Carlos de Madrid (Protocol HCSC/22/005-E).

3. Results

During the study period, 23,278 patients were included (Fig. S1), with a mean age of 78.29 years (SD 8.09), of whom 10,196 (43.8 %) were male. After evaluation in the ED, 5763 (24.76 %) patients were admitted to hospital.

The results of the univariate analysis comparing the characteristics of patients based on admission or discharge highlight that older age and functional impairment were significantly associated with a higher probability of admission. No clinically significant differences were observed between the patients in the training, validation, and test cohorts for any of the variables analysed.

Table 1A and Fig. 1A show the performance of various statistical methods for predicting admission in Model 1, with the RF model achieving the highest AUC (0.85) in the test sample. Table 1B and Fig. 1B present the results for Model 2, in which RF again demonstrated the highest AUC. The contribution of each feature to the RF model of admission predictions for both models is shown in Fig. 2, using SHAP values for the derivation and test sets. For Model 1, haemoglobin and leukocyte counts were the most important predictors, while for Model 2, the key clinical variables were mode of arrival (ambulance), oxygen saturation, and systolic blood pressure.

There were significant differences in the AUC between the RF model and those predicted by KNN, SVM, logistic regression, and GBC. However, no significant differences were observed when comparing RF to the DT and XGBoost models. Sensitivity analysis was also performed: for the DT model, the 95 % CI ranged from 0.056 to 0.095, and for XGBoost, from 0.159 to 0.207. These results indicate differences between the supervised learning techniques, confirming that the RF model of Model 1 is the most appropriate for predicting hospitalisations. Similarly, when comparing the AUC of Model 2, significant differences were observed

Table 1. Performance of the risk models developed for hospital admission.

A. Evaluation metrics of the model 1 (including analytical variables)					
	Derivation sample				
	Sensitivity	Accuracy	Precision	AUC (95 % CI)	Cut-off point
Random forest	0.88	0.72	0.46	0.86 (0.85–0.87)	0.55
Decision tree	0.83	0.75	0.49	0.85 (0.84–0.86)	0.53
KNN	0.94	0.96	0.92	0.98 (0.97–0.99)	0.16
SVM	0.76	0.77	0.52	0.84 (0.83–0.85)	0.38
Logistic regression	0.67	0.74	0.49	0.78 (0.77–0.79)	0.46
Gradient boosting classifier	0.83	0.83	0.61	0.90 (0.89–0.91)	0.47
XGBoost	0.88	0.91	0.79	0.96 (0.95–0.97)	0.52
	Test sample				
	Sensitivity	**Accuracy**	**Precision**	**AUC (95 % CI)**	**Cut-off point**
Random forest	0.88	0.71	0.45	0.85 (0.84–0.86)	0.57
Decision tree	0.80	0.73	0.47	0.84 (0.82–0.85)	0.53
KNN	0.56	0.74	0.47	0.74 (0.72–0.75)	0.18
SVM	0.72	0.75	0.49	0.81 (0.80–0.83)	0.36
Logistic regression	0.67	0.75	0.49	0.78 (0.76–0.79)	0.59
Gradient boosting classifier	0.71	0.76	0.51	0.83 (0.82–0.84)	0.42
XGBoost	0.69	0.79	0.55	0.84 (0.83–0.86)	0.42
B. Evaluation metrics of the model 2 (not considering analytical variables).					
	Derivation sample				
	Sensitivity	Accuracy	Precision	AUC (95 % CI)	Cut-off point
Random forest	0.79	0.74	0.48	0.84 (0.83–0.85)	0.50
Decision tree	0.76	0.73	0.47	0.82 (0.81–0.83)	0.59
KNN	0.94	0.96	0.90	0.99 (0.98–1.00)	0.31
SVM	0.74	0.81	0.59	0.85 (0.84–0.86)	0.46
Logistic regression	0.66	0.73	0.48	0.78 (0.77–0.79)	0.46
Gradient boosting classifier	0.77	0.77	0.53	0.85 (0.84–0.86)	0.47
XGBoost	0.82	0.86	0.69	0.92 (0.91–0.93)	0.49
	Test sample				
	Sensitivity	**Accuracy**	**Precision**	**AUC (95 % CI)**	**Cut-off point**
Random forest	0.75	0.72	0.46	0.80 (0.79–0.82)	0.49
Decision tree	0.70	0.70	0.43	0.78 (0.76–0.79)	0.48
KNN	0.58	0.70	0.42	0.72 (0.71–0.74)	0.41
SVM	0.58	0.73	0.45	0.73 (0.71–0.75)	0.40
Logistic regression	0.65	0.73	0.46	0.77 (0.76–0.79)	0.45
Gradient boosting classifier	0.68	0.72	0.45	0.78 (0.76–0.79)	0.39
XGBoost	0.61	0.75	0.49	0.78 (0.76–0.80)	0.38

KNN: K-Nearest Neighbors; SVM: *Support Vector Machines*. AUC: Area Under Curve. CI: Confidence Interval.

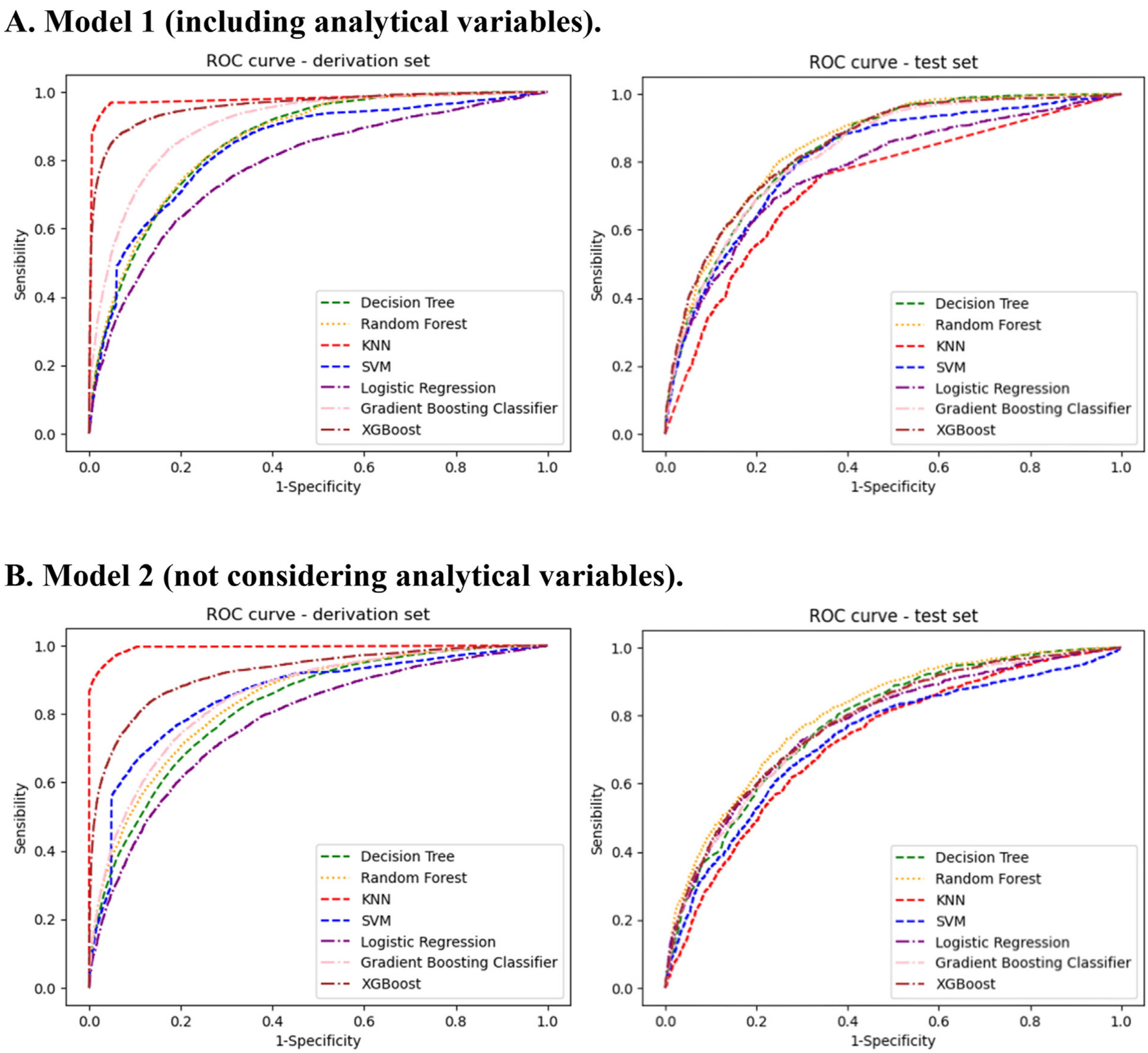


Fig. 1. ROC curve for the derivation and test set.

between the RF model and other techniques, further supporting the RF method as the most suitable. A comparison of the two RF models (Model 1 and 2) revealed a 95 % CI of 0.018–0.048, indicating that Model 1, which includes blood test variables, provides statistically significant improvement in the prediction of hospitalisation.

Finally, a risk score was developed based on RF Model 1, as it offered the best sensitivity for the prediction of hospitalisation. This model included the following variables: mode of arrival to the ED, haemoglobin, leukocytes, oxygen saturation, international normalized ratio, creatinine, platelets, glucose, arrival without referral from a primary care physician, sodium, prothrombin time, C-reactive protein, potassium, Charlson comorbidity index, systolic blood pressure, diastolic blood pressure, age, heart rate, and sex. The probability of admission was categorised based on percentiles, with the optimal cut-off point calculated for each continuous variable. Table 2 presents the sensitivity and specificity for each established category. Four risk groups were created, using patients with a score <0.18 as the reference group, in which the risk of hospitalisation was 1.94 %. This risk increased with higher scores. Fig. 3 shows the calibration performance for both the derivation and test sets.

4. Discussion

The results of our study indicate a high admission rate among older patients seen in EDs of Spanish hospitals, with this rate increasing with age. A recent European study involving patients aged 65 years and older visiting the ED reported a hospitalisation rate of 52 % (8). Hospitalisation rates for

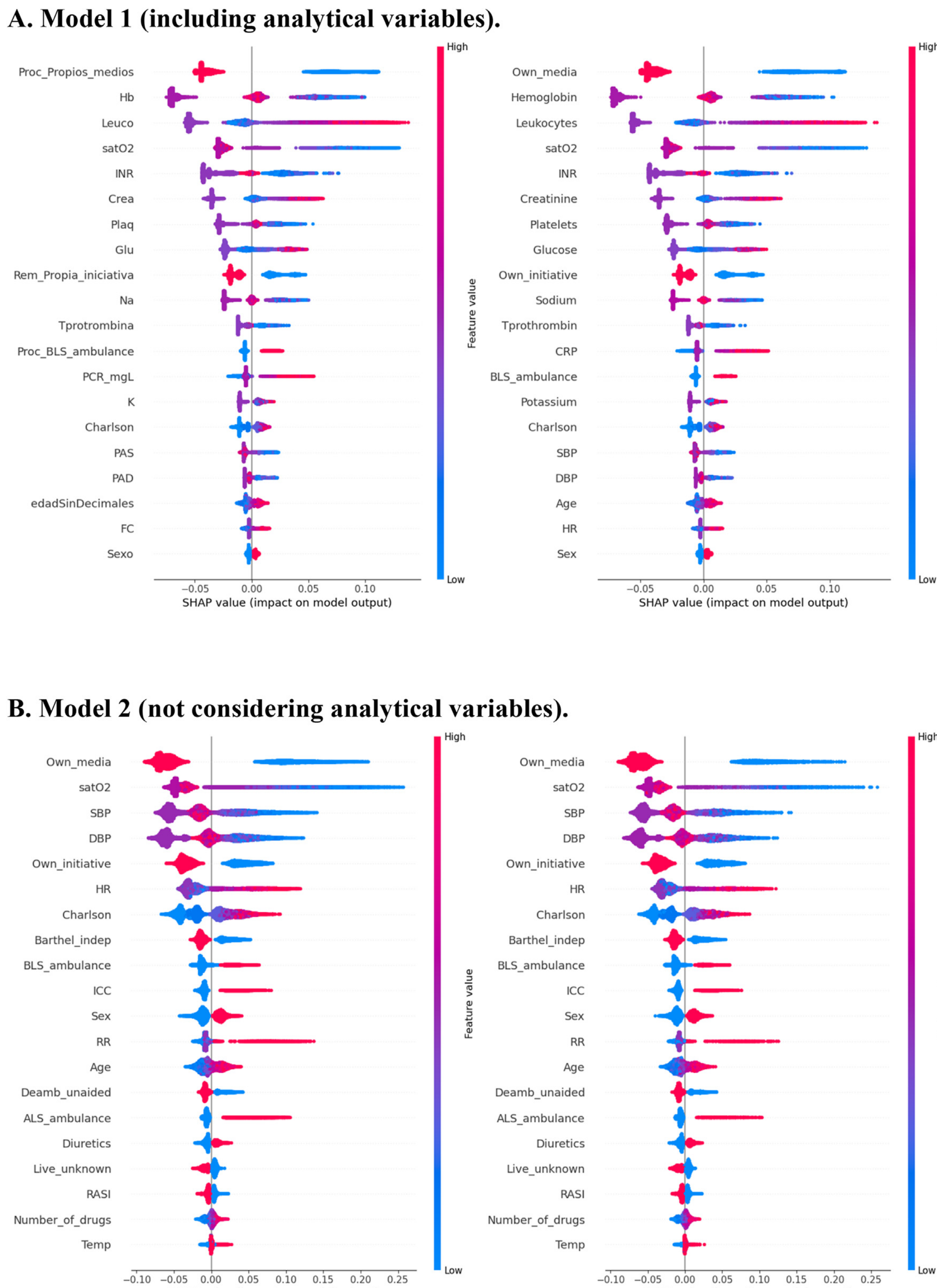


Fig. 2. The contribution of each feature to the prediction of the Random Forest for the derivation and test set using SHAP. On the left there are the results of the derivation sample; on the right, there are those of the test sample. The weight of each variable for the model is ordered from top (highest) to bottom (lowest). For dichotomous variables, the left of the axis means "no", and the right "yes". The red colour indicates a greater probability of admission, while blue indicates a lower probability of admission.

*Table 2. **Sensitivity and specificity according to different cut-off points in the Derivation and test samples.** TPR: True Positive Rate. TNR: True Negative Rate.*

	Derivation sample				Test sample			
	Sensitivity	Specificity	TPR	TNR	Sensitivity	Specificity	TPR	TNR
Score ≥ 0.18	0.98	0.45	0.37	0.98	0.98	0.44	0.36	0.98
Score ≥ 0.55	0.82	0.73	0.50	0.93	0.82	0.73	0.49	0.93
Score ≥ 0.67	0.57	0.89	0.63	0.86	0.57	0.88	0.62	0.86

older ED patients vary between 20 % and 65 % across different studies [8,25]. Furthermore, up to one quarter of all patients presenting to the ED are ≥65 years of age [26,27]. These figures pose significant challenges for hospital management.

Our study developed a tool for predicting hospitalisation in a complex population, specifically elderly patients, based on factors such as age, sex, comorbidities, vital signs, and analytical variables obtained at the time of ED presentation. This model classifies patients' risk of hospitalisation from 2 % to 57 %. It demonstrates excellent sensitivity, reaching up to 0.88, making it a valuable tool for identifying cases requiring hospitalisation. Other similar studies have developed prediction tools specifically for emergency hospitalisations, effectively identifying cases that do not require monitoring or follow-up [28]. However, unlike our models, the target population was not specifically over 65 years of age, logistic regression was the most commonly used method, and the outcome variable was, in our opinion, very heterogeneous as it was not concentrated in the probability of admission. The primary advantage of our model is its applicability in large numbers of patients typically seen in the ED, providing a straightforward way to identify the proportion of high-risk patients. This enables bed planners to anticipate bed needs in advance, allowing sufficient time to make decisions and organise hospital resources, thereby reducing delays in patient admissions and alleviating ED overcrowding. A significant limitation of the model is the reliance on analytical variables, which may delay the availability of information. We developed an alternative model that excluded analytical parameters, but its sensitivity was lower than when these variables were included.

Predicting hospital admissions in this specific population allows healthcare providers to allocate proactive resources to those in greater need, potentially enhancing the capacity and cost-effectiveness of interventions [29]. Currently, most hospitals rely on simple heuristics for short-term forecasts of emergency admissions, typically based on rolling averages for each day of the week [30,31]. Our clinically useful prediction model demonstrates good sensitivity for hospital admissions among older patients. The methods and models we employed can be generalised and implemented across most healthcare systems with electronic health statistics, as they utilize variables that are readily available in electronic records.

A recent systematic review [32] of predictive models for detecting ward admissions from the ED, which included 14 articles, found that logistic regression is the most commonly used predictive model, achieving AUC values between 0.75 and 0.92. Overall, the studies included suggest that these models can effectively predict patient ward admissions, demonstrating strong relationships between sensitivity and specificity.

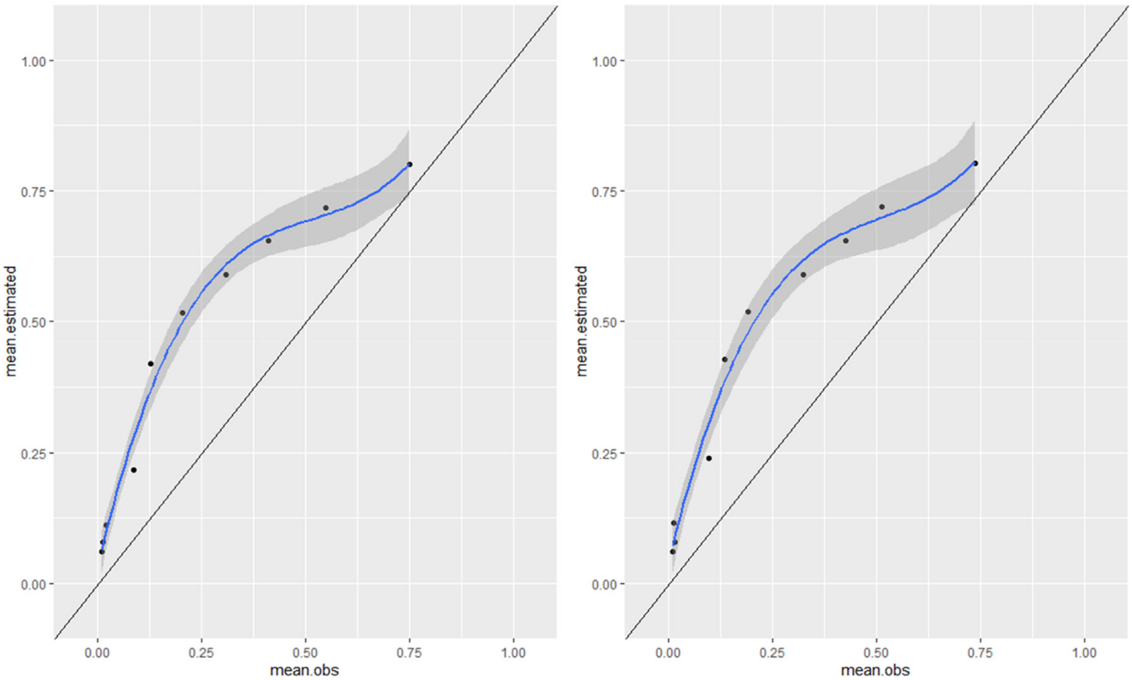
However, a key limitation of logistic regression is its assumption of linearity between the dependent and independent variables. In linear regression, the relationship between these variables is straightforward; however, logistic regression requires independent variables to be linearly related to the log probabilities. This makes it challenging to capture complex relationships. More advanced and compact algorithms, such as neural networks, can often outperform logistic regression in this context.

Utilizing other mathematical tools to develop these types of models can enhance their sensitivity and contribute to improving the quality of care in the ED. Better internal management can be achieved by accurately predicting the number of admissions, which helps reduce the likelihood of ED overcrowding through effective planning and alleviates the burden on healthcare systems.

ML applications for hospital management are still under-studied. A recent study presented a prediction pipeline that utilizes live electronic health records in the ED of a UK teaching hospital to generate short-term, probabilistic forecasts of emergency admissions for older patients over the next 12 months [14]. This approach facilitates the selection of individuals for targeted interventions, including personalised care plans, and helps reduce the demand for hospital care.

Classic admission prediction models often fail to account for the variable nature of ED care and cannot adapt to the diverse mix of cases seen simultaneously. In hospitals with electronic health records, there is a valuable opportunity to leverage data entered by professionals during routine clinical

A. Model 1 (including analytical variables).



B. Model 2 (not considering analytical variables).

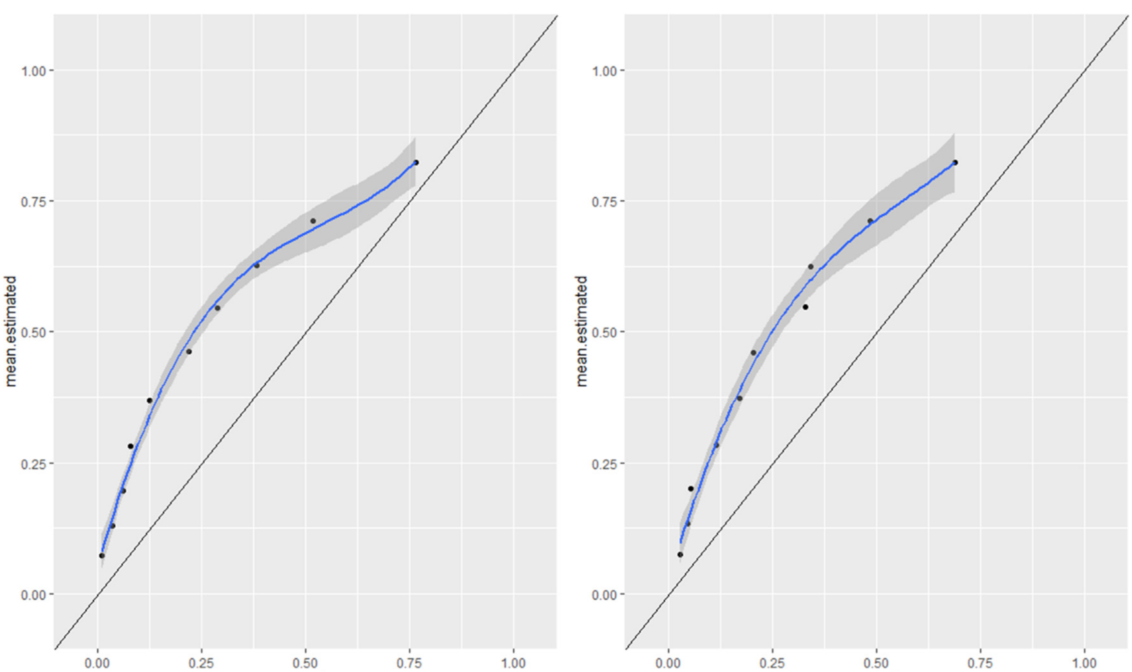


Fig. 3. Calibration performance in derivation and test sets.

practice to generate short-term predictions of bed demand. This approach could assist bed assignment teams in optimizing available capacity, reducing or even increasing cancellations of elective admissions, if circumstances allow.

ML is particularly attractive for such predictions because it allows the incorporation of weak predictor variables to create a robust prediction model [33]. Studies employing classical methodologies, such as Bayesian or linear regression, typically use variables such as arrival characteristics, triage data, previous visit history, and pathological conditions [34,35]. Hong et al. [33] demonstrated that including laboratory test results and procedures enhances predictive power, while El-Bouri et al. [31] successfully predicted which medical specialty patients would be admitted.

A prediction tool that provides the probability of admissions over a specified time period is more useful than one that estimates the probability of admission at the individual patient level. Furthermore, when making predictions within a post-prediction time window, it is essential to consider the number of patients who are not currently in the ED but are expected to arrive and be admitted during that period [13].

In an environment with limited resources, the benefits of implementing ML must be carefully weighed against the associated costs. We posit that improved information could enhance the ability of bed planners to manage the complexities of patient flow. Ultimately, overcrowding in EDs stems from systemic issues, such as bottlenecks and capacity constraints [35], which can lead to adverse events for patients and safety concerns during their care in the ED.

Our study has several limitations. First, the 52 Spanish EDs participating in the study were not randomly selected but rather expressed interest in participating. However, the broad representation across territorial levels (12 of the 17 autonomous communities were included) and hospital types (university, high-tech, and regional hospitals) suggests that any bias is likely minimal. Second, the analysis presented here was conducted globally rather than by nosology groups. Thus, the findings may be influenced by certain processes that vary with the sex or age of the patients. Nonetheless, our design captures the full spectrum of patients seen, is not limited to a single disease or group of diseases, and provides a comprehensive overview.

Third, this study is a secondary analysis of a multipurpose cohort, which means that the reported associations may be affected by factors not accounted for in the cohort design. Therefore, the findings should be regarded as hypothesis-gene rating and should be validated by studies specifically designed for this purpose. Finally, some variables, such as laboratory results and constants, are not fully captured in the database, necessitating data imputation for analysis. This can affect data quality and the predictive ability of the model. Additionally, there is a notable imbalance in the target variable, requiring the classes to be balanced by randomly replicating instances of the minority class.

5. Conclusion

The present study describes the development of a high-sensitivity score for predicting hospital admissions in older patients attending the ED. This score enhances the ability of bed planners to manage patient flow to prevent ED overcrowding, which can jeopardize patient safety and disrupt the healthcare system. It is expected that the models will be externally validated to ensure their performance for implementation in electronic health records and decision support systems.

Availability of data and materials

The datasets used and/or analysed during the present study are available from the corresponding author upon reasonable request.

Funding

The study was not funded.

Conflic of interest

All authors reported no conflicts of interest.

Supplementary material

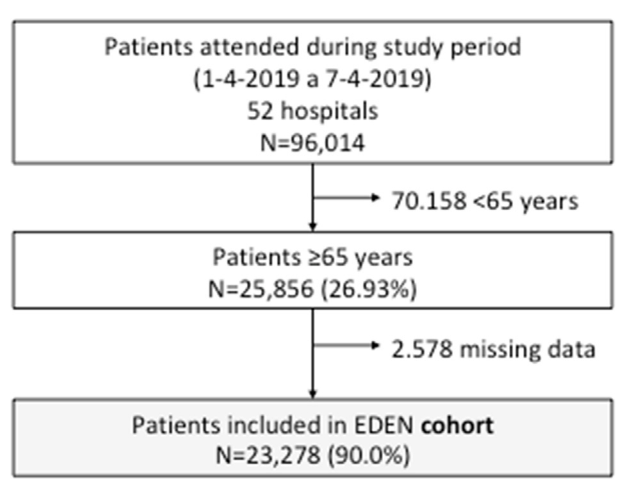


Fig. S1. Flow chart of case inclusion.

Appendix 1

Local investigators of the SIESTA network are listed in Appendix 1: Hospital Clínico San Carlos, Madrid: Eric Jorge García Lamberechts, Paula Queizán García, Andrea B Bravo Periago, Blanca Andrea Gallardo Sánchez, Alejandro Melcon Villalibre, Sara Vargas Lobé, Laura Fernández García, Beatriz Escudero Blázquez; **Hospital Universitario Infanta Cristina, Madrid:** Ángel Iván Diaz Salado, Alicia Fuente Gaforio, Cristina Güemes de la Iglesia, Beatriz Honrado Galán, Sandra Moreno Ruíz; **Hospital Santa Tecla, Tarragona:** Enrique Martín Mojarro, Sílvia Flores Quesada, Osvaldo Jorge Troiano Ungerer; **Hospital Universitario de Canarias, Tenerife:** Aarati Vaswani- Bulchand, Patricia Eiroa-Hernández; **Hospital Norte Tenerife**: Montserrat Rodríguez-Cabrera; **Hospital General Universitario Reina Sofia, Murcia**: Pascual Piñera Salmerón, María Consuelo Quesada Martínez, Marta Isabel Gómez Gómez, Yurena Reverte Pagán, Lorena Bernabé Vera, Juan José López Pérez; **Hospital Universitario del Henares, Madrid**: Raquel Santos Villanueva, Marta Lozano Berdasco, David Ampuero Martinich; **Hospital Clinic, Barcelona:** Sonia Jiménez, Sira Aguiló Mir, Francesc Xavier Alemany González, María Florencia Poblete Palacios, Claudia Lorena Amarilla Molinas, Ivet Gina Osorio Quispe, Sandra Cuerpo Cardeñosa; **Hospital General Universitario de Elche**: Matilde González Tejera, Ana Puche Alcaraz, Cristina Chacón García; **Hospital Universitario y Politécnico La Fe, Valencia:** Leticia Serrano Lázaro, Javier Millán Soria, Jésica Mansilla Collado, María Bóveda García; **Hospital General Universitario Dr. Balmis, Alicante:** Pere Llorens Soriano, Adriana Gil Rodrigo, Begoña Espinosa Fernández, Mónica Veguillas Benito, Sergio Guzmán Martínez, Gema Jara Torres, María Caballero Martínez; **Hospital Universitario de Bellvitge, L'Hospitalet de Llobregat, Barcelona:** Javier Jacob, Ferran Llopis, Elena Fuentes, Lidia Fuentes, Francisco Chamorro, Lara Guille, Nieves López; **Hospital de la Axiarquia de Velez, Malaga**: Lucía Zambrano Serrano, Rocío Muñoz Martos, Coral Suero Méndez; **Hospital Regional Universitario de Málaga:** Manuel Salido Mota, Valle Toro Gallardo, Antonio Real López, Lucía Ocaña Martínez, Esther Muñoz Soler, Mario Lozano Sánchez, Eva Fraguero Blesa; **Hospital Santa Barbara, Soria:** Fahd Beddar Chaib, Rodrigo Javier Gil Hernández; **Hospital Valle Pedroches, Pozoblanco, Cordoba:** Jorge Pedraza García, Paula Pedraza Ramírez; **Hospital Reina Sofia, Córdoba:** F. Javier Montero-Pérez, Carmen Lucena Aguilera, F. de Borja Quero Espinosa, Angela Cobos Requena, Esperanza Muñoz Triano; Inmaculada Bajo Fernández, María Calderón Caro, Sierra Bretones Baena; **Hospital Universitario Gregorio Marañon, Madrid:** María Fernández Cardona, Leonor Andrés Berián, María Esther Martinez Larrull, Susana Gordo Remartinez, Ana Isabel Castuera Gil, Laura Martín González, Melisa San Julian Romero, Montserrat Jiménez Lucena; **Hospital Universitario De Burgos:** Amanda Ibisate Cubillas, Monica de Diego Arnaiz, Verónica Castro Jiménez, Lucía González Ferreira, Rocio Hernando González; **Complejo Asistencial Universitario de León:** Marta Iglesias Vela, Mónica Santos Orús, Rudiger Carlos Chávez Flores, Alberto Álvarez Madrigal, Albert Carbó Jordá, Héctor Lago Gancedo, Miguel Moreno Martín, Alberto Alvarez Madrigal; **Hospital Universitario Morales Meseguer, Murcia:** Rafael Antonio Pérez-Costa, María Rodríguez Romero, Ana Barnes Parra, Sara Sánchez Aroca; **Hospital Francecs de Borja de Gandía:** Alicia Sara Knabe, Andrea Cantos López, Rafael Terol Calvo, Mario Velasco Garcia; **Hospital Universitario Severo Ochoa,** Leganés: María José Hernández Martínez, Ana Benito Blanco, Vanesa Abad Cuñado, Julia Martínez-Ibarreta Zorita, Irene Cabrera Rodrigo; **Hospital Universitario Virgen Arrixaca, Murcia:** Eva Quero Motto, Nuria Tomas Garcia, Laura Bernal Martínez, Miguel Parra Morata; **Hospital Universitario Lorenzo Guirao, Cieza:** Carmen Escudero Sánchez, José Joaquín Giménez Belló; **Hospital Josep Trueta, Girona:** Maria Adroher Muñoz, Ester Soy Ferrer, Eduard Anton Poch Ferrer; **Hospital de Mendaro, Gipuzkoa:** Jeong-Uh Hong Cho; **Hospital Miguel Servet, Zaragoza:** Patricia Trenc Español, Fernando López López, Jorge Navarro Calzada, Belén Gros Bañeres, Cristina Martín Durán, María Teresa Escolar Martínez-Berganza, Iciar González Salvatierra; **Hospital Comarcal El Escorial, Madrid**: Sara Gayoso Martín; **Hospital Do Salnes, Villagarcía de Arosa:** Goretti Sánchez Sindín; **Hospital de Barbanza. Ribeira, A Coruña:** Azucena Prieto Zapico; Jésica Pazos González; **Hospital del Mar, Barcelona**: Isabel Cirera Lorenzo, Patricia Gallardo Vizcaíno, Margarita Puiggali Ballard, M Carmen Petrus Rivas; **Hospital Santa Creu y Sant Pau, Barcelona:** Aitor Alquezar Arbe, Adriana Laura Doi Grande, Sergio Herrera Mateo, OlgaTrejo Gutiérrez, Paola Ponte Márquez, Carlos Romero Carrete, Sergio Pérez Baena; **Hospital de Vic:** Lluís Llauger; **Hospital del Nalón, Langreo:** Ana Murcia Olagüenaga, Sayoa Francesena González, Cesar Roza Alonso; **Hospital Altagracia, Manzanares:** Ivana Tavasci Lopez, Edmundo Ramon Figuera Castro; **Hospital Nuestra Señora del Prado de Talavera de la Reina:** Ricardo Juárez González, Mar Sousa, Laura Molina, Mónica Cañete; **Hospital Universitario Vinalopó, Elche:** Esther Ruescas, María Martínez Juan, María José Blanco Hoffman, Pedro

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