Ladios-Martin Mireia (Orcid ID: 0000-0002-6127-7746)

Cabañero-Martínez María José (Orcid ID: 0000-0002-8333-2988)

Title: Predictive inpatient falls risk model using Machine Learning

Authors:

Ladios-Martin, Mireia MSN, RN [a]; Cabañero-Martínez, Maria-José PhD, MSN, RN [b], Fernández-de-Maya, José PhD, MSN, RN [c], Ballesta-López, Francisco-Javier MSN, RN [d]; Belso-Garzas, Adrián MS [e]; Zamora-Aznar, Francisco-Manuel MS [f]; Cabrero-Garcia, Julio PhD [g]

Affiliation:

- [a] Ribera Salud
    - Address: Edificio Sorolla Center. Avda.Cortes Valencianas, 58. 46015. Valencia (Spain).
- [b-g] Nursing Department. University of Alicante
    - Address: Carretera San Vicente del Raspeig s/n. 03690. San Vicente del Raspeig – Alicante (Spain)
- [c-d] University Hospital of Vinalopo
    - Address: C/Tonico Sansano Mora, 14, 03293. Elche-Alicante (Spain)
- [e-f] Riberasalud Tecnologia
    - Address: Carrer Santiago Ramón y Rajal, nº 43. Elche-Alicante (Spain)

Corresponding author:

- **Author:** Ladios-Martin, Mireia
- **Telephone:** +34 639 871 621
- **Email:** mladios@riberasalud.es

Conflicts of interest for all authors: None declared

Funding sources: No external funding

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1111/jonm.13760

Ethical approval

Ethical approval number: CI2018-22

Name of review board: Research Commission of the University Hospitals of Torrevieja and VInalopó (Spain)

Date: 08/28/2018

Abstract

Aim

To create a model that detects the population at risk of falls taking into account fall prevention variable and to know the effect on the model´s performance when not considering it.

Background

Traditionally, instruments for detecting fall risk are based on risk factors, not mitigating factors. Machine learning (ML), which allows working with a wider range of variables, could improve patient risk identification.

Methods

The sample was composed of adult patients admitted to the Internal Medicine service (total, n=22515; training, n=11134; validation, n=11381). A retrospective cohort design was used and we applied ML technics. Variables were extracted from electronic medical records (EMR).

Results

The Two-Class Bayes Point Machine algorithm was selected. Model-A (with fall prevention variable) obtained better results than Model-B (without it) in sensitivity (0.74 vs 0.71), specificity (0.82 vs 0.74) and AUC (0.82 vs 0.78).

Conclusions

Fall prevention was a key variable. The model that included it detected the risk of falls better than the model without it.

Implications for Nursing Management

We created a decision-making support tool that helps nurses to identify patients at risk of falling. When it´s integrated in the EMR, it decreases nurses' workloads by not having to collect information manually.

Keywords: Data mining, Machine Learning, Falls, Risk Assessment, Patient Safety

Background

Despite the efforts made in recent years, falls, defined as an unplanned descent to the ground with or without injury to the patient (Ganz et al., 2013), remain a challenge in hospitals. While figures vary across studies, it is estimated that internationally, 1.6 to 5.4 falls occur per 1000 days of hospital stay (Cho et al., 2019; Yokota et al., 2017; de Souza et al., 2019; Anderson et al., 2015; García-Hedrera et al., 2021; Luzia et al, 2018; Menéndez et al., 2013; Orrego 2016). Of these, approximately 71.9% of patients will suffer no harm, 25.5% will suffer a minor injury and 2.6% a moderate or severe type (NHS 2017). Operational cost for fallers with serious injuries, as compared with nonfallers is $13.316 more and a stay 6.3 days longer (Wong et al., 2011). Therefore, falls have both a health and economic impact.

Why patients fall is a multifactorial event, stemming from the interaction between patients' intrinsic factors (incontinence, sensory deficiencies, etc.), environmental factors (architectural barriers, etc.), and the subject's own behaviour (Evans et al., 2001). Added to these, are factors resulting from professional-patient interaction in healthcare environments increasing or decreasing the risk (Oliver et al., 2010), for example, early rehabilitation that is assisted-supervised (or not) after a surgical intervention or assisted toiling (or not). Overall, there is a consensus that hospitalisation increases the risk of suffering a fall (Anderson et al., 2015): patients indeed find themselves in an unknown environment due to a state of fragility and are subjected to different procedures and treatments that may impair their capacity.

Falls risk screening of all hospitalised patients constitutes a major measure of prevention that is supported by extensive evidence and a broad consensus (RNAO, 2017). The tools that have traditionally been applied for the early detection of patients at risk of falls include both patient- and practitioner-reported scales, such as the Morse Falls Scale (Morse et. al, 1982), Stratify (Oliver et. al, 1997) or the Downton Scale (Downton, 1993), as well as physical performance tests, such as the Timed Up and Go (Podsiadlo et. al, 1991), the Berg Balance Scale (Berg et.al, 1992) or the Short Physical Performance Battery (Guralnik, 1994). The first ones usually include a battery of fall-predicting variables and discriminate sufficiently well between fallers and nonfallers (Oliver et al., 2010) but they present some weaknesses: they have limited external validity (Haines et al., 2007); they need to be applied whenever the patient's condition changes to ensure that the results reflect the person's current situation (RNAO, 2017) and they may not include all related risk factors because they try to be easy to use (Callis, 2016). On the other hand, physical performance tests can also be used and have been shown to be good predictors of falls risk. However, their use requires specific equipment or conditions (stopwatch, chair, large space) and are more time-consuming compared to the initial ones, so they are of little use in acute inpatient units.

Some of these limitations of traditional instruments could be solved by incorporating artificial intelligence (AI) techniques, such as machine learning (ML). Notable among ML's multiple applications is its predictive power, which can be used in preventive strategies, streamlining processes and assisting in decision-making. The development and integration of these types of AI-based predictive models into electronic medical records (EMR) enables the automatic analysis of a greater range of variables (structured or not structured data), dispensing with the need to retrieve and evaluate the latest information available manually. In other words, in the healthcare environment, these tools can help to identify and follow up at-risk populations (Saria et al., 2018), providing valuable information in real time, without increasing the workload of healthcare professionals.

To date, several studies have employed ML to detect fall risks or fall risks with injury in hospitals. Most of these studies make use of the data available in the EMR to develop their models (Marschollek et al., 2012; Cho et al., 2019; Yokota et al., 2017; Lindberg et al., 2020; Nakatani et al., 2020, Wang, 2019), although we can also find studies that use a motion tracking system with cameras that capture patients' physical performance tests (Eichler et al., 2022). Models based on EMR variables typically include the following types of variables: demographic characteristics, admission information, assessment information, clinical data, and organizational characteristics. Among the variables that have traditionally been incorporated into predictive models of fall risk, the variable fall prevention (FP), a mitigating factor defined as a series of healthcare acts performed by professionals to prevent the patient from suffering a fall during hospitalisation has been particularly controversial, as its non-inclusion could mask the performance of the model. (Myers et al., 2003). To the best of our knowledge, only the model developed by Cho et al. (2019) has included this variable in its final configuration

The above-mentioned advantages of AI techniques and the incorporation of the FP variable in the risk assessment will facilitate the identification of patients most likely to fall in the hospital. Therefore, in the present study we propose to use ML to create a model that detects the population at risk of falls taking into account this variable. As a secondary objective we propose to know the performance of the model by not including the FP variable in it.

Methods

Setting

The study was conducted on patients treated by the Internal Medicine Service of two public university hospitals, with 230 and 277 beds, respectively. All study variables were obtained from the EMR.

Business and Data understanding

In-hospital falls were defined operatively as a "fall" record under the EMR’s nursing incidences section. If patients suffered more than one fall during their stay, only the first was included. All falls, regardless of the type of ensuing injury were included. To correct any possible bias due to under-reporting in the specific incidents section, cases were retrieved using a search algorithm that located records linked to "falls" in the nursing records’ free text of the EMR. The potential cases identified by such an algorithm were reviewed by an expert. Confirmed cases were included in the group of fallers (42.5% of the cases of the total sample used to design the model).

Design

A retrospective cohort design was used to construct and validate models directed towards classifying patients at risk of falls or not.

Due to the retrospective nature of the study, i.e., based on available data, we selected all eligible cases during one year for the model training sample and the following year for the validation sample. The cumulative incidence of falls was slightly above 200 cases in both samples. According to the widely accepted criterion of at least ten events per variable, the size of both samples is adequate for a model with 20 predictors. In addition, we calculated confidence intervals (IC) for the measures selected to assess the models' performance (Collins et al., 2015).

Data Preparation

The eligible population met the following criteria: 16 years of age and above, admitted to the Internal Medicine service, with a hospital stay equal to 24 hours or longer.

The data collection period was 1 January 2018 to 31 December 2019. The total sample was 22515 subjects. The sample between 1 January and 31 December 2018 (n=11134) was used to train the models, and the sample between 1 January and 31 December 2019 (n=11381) was used to validate the models. (Figure 1).

We conducted a literature review to identify predictors of falls. A total of 91 variables were selected. Next, the possibility of obtaining these variables from the EMR was evaluated, and the criteria to do so were defined according to each variable for both the "fallers" and the "nonfallers". The values of each variable were extracted based on one of the following temporal strategies: data from previous hospitalisations or data generated during admission. When the variable data was generated during the admission, the value was obtained at the time of admission or the closest data (or its accumulated value when applicable) to the fall (or to the day the fall was expected to happen (median in days to fall). Details of the variables can be found in the Appendix. Of the total variables, 6 were discarded because a large number of values were missing (BMI, weight loss, bone density and diagnoses at admission: arrhythmias, knee prosthesis and vestibular pathology).

The extracted data was then processed to generate a database that would help to select the algorithm. Four variables had missing values, all in both samples: hemoglobin, 168 (1.46%) and 137 (1.16%), family support, 169 (1.47%) and 138 (1.17%), ambulation, 12 (0.1%) and 65 (0.55%), and incontinence, 51 (0.44) and 66 (0.56%) in the training and validation samples, respectively. In total, 400 (3.47%) observations had some missing value in the training sample and 406 (3.44%) in the validation sample. Given the small percentage (<5%) of missing values in both samples, we performed a complete case analysis (we eliminated all observations with any missing value), as supported by the literature (Madley-et al., 2019). To balance the fallers and nonfallers, the Synthetic Minority Over-Sampling Technique (SMOTE) was used as it has shown to improve accuracy in minority classes (Chawla et al., 2002)

Both samples were compared (Table 1) with the Student's t-test (continuous variables), the Z-test of two proportions (binary variables) and the Chi-square test (categorical variables). The

95% IC of the differences in means and proportions and the exact statistical significance value of the Chi-squared tests were provided.

Model Development

The performance of 10 classification algorithms available in Azure®ML were evaluated according to the study's objective. The criteria we used for selection was: accuracy, precision, recall, F1-score and area under the curve (AUC) (Table 2).

Model-A (with the FP variable)

In accordance with the main objective of our study, the variable FP was included in Model-A. This variable was defined as the recording, in standardised or natural language, of nurses' usual practice in hospitals, in accordance with the clinical practice guidelines (RNAO, 2017) and comprising tasks such as: risk reduction in the environment (low beds, restricted use of bed railings, obstacle-free space, sufficient lighting, etc.), falls risk education and prevention measures, provision of mobility aids, the programming of accompaniment, or on-demand personal hygiene and cleaning assistance, among others.

To develop the model, we proceed in two phases. The first phase focused on training Model-A, using the sample from January to December 2018 (n=11134). Variables that did not improve accuracy or whose improvement was minimal were removed from the model. The process was repeated iteratively until optimal results were achieved. The second phase centred on validating Model-A, using the sample from January to December 2019 (n=11381).

Model-B (without the FP variable)

To train and validate Model-B, we used the same process and dataset as in Model-A, but in accordance with the secondary objective of our study, the variable FP was excluded.

Once the definitive models were created using the training sample, the system automatically provided the average variable weights consisting of the contribution of each variable to the model. Subsequently, each model's performance was evaluated using the validation dataset, and the measures of sensitivity, specificity, F1-score, Youden index and AUC were calculated.

To develop the models, Microsoft's cloud platform, Azure®, was used. The R software® (v. 3.4.2) was employed for the rest of the statistical analysis.

The personal data were anonymized and the current regulations were followed in accordance with the Spanish Law on Protection of Personal Data and Guarantee of Digital Rights

Results

The total sample was 22515 patients with an average age of 71 years, those aged over 72 accounting for 58.5 % (n=13180) of the sample. A total of 56.4% (n=12696) were male, 32.5% (n= 7315) were of foreign nationality and 86 % (n= 19266) didn´t live alone. The mean stay was 7 days; 6.54% (n= 1469) had suffered a previous fall, and the most common morbidity was chronic obstructive pulmonary disease (COPD) (31.93%, n=7189), followed by diabetes mellitus (DM) (27.34%, n=6156) and congestive heart failure (CHF) (26.09%, n=5519) (Table 1).

Falls rate per 1000 days of stay was 2.69. Both samples were similar (Table 1), with most variables balanced between the two groups. The largest differences were in the diagnosis of fall risk (31.15 vs 27.26%), FP (20.24 vs 17.64%) and history of diabetes (28.22 vs 26.28%).

The performance of the 10 ML algorithms can be observed in Table 2. The Two-Class Bayes Point Machine algorithm was selected because it displayed the best results in the accuracy measure, as the Logistic Regression algorithm, but overpassed it in the measures of recall, F1-score and AUC.

Model-A was composed of 13 variables and Model-B of 22 variables. Each model assigned different average weights to the different variables based on the training sample. In Model-A (Figure 2A), 3 variables contributed more than 80% of the average weight. These variables were, in decreasing order: FP, age and days of psycholeptics treatment. The FP variable accounted for almost twice as much as the age variable. In Model-B (Figure 2B), 10 variables contributed more than 80% of the average weight. These variables were, in decreasing order were: days of stay, incontinence (Norton), days of psycholeptics treatment, sex, arthritis (admission diagnosis), place of birth, history of diabetes, risk for falls (nursing diagnosis) haemoglobin lab value and history of chronic obstructive pulmonary disease. Except for the variables FP and days of antiparkinsonian treatment, the remaining Model-A variables were also part of Model B.

The results obtained by validating Model-A and Model-B are presented in Table 3 and Figures 3A and 3B. Model-A generated the following statistics: sensitivity 0.74 (0.68-0.79), specificity 0.82 (0.81-0.83), F1 score 0.14, Youden index 0.55 and AUC of 0.82 (0.79-0.85). Model-B presented the following results: sensitivity0.71 (0.65-0.78), specificity 0.74 (0.73-0.75), F1 score 0.9, Youden index 0.45and AUC of 0.78 (0.74-0.82). The models share their IC for the area under the curve and sensitivity, but not for specificity.

Discussion

To detect the risk of falls, some approaches are based on classical statistical methods and more recently, others also employ AI techniques. We have developed a predictive model for the detection of patients at risk of falling using AI techniques with a good psychometric performance and including a critical variable such as FP. Furthermore, the comparison of models with and without this variable allows us to demonstrate its importance in the detection of people at risk and therefore in the performance of the model itself. This demonstrates the need to include it, or at least consider it, in any predictive model that is developed.

AI application and the use of FP variable is rare, only included by Cho et al. (2019) in its final configuration, in which this variable came third in terms of importance after fall risk assessment (Hendrich II scale) and nursing assessment-diagnoses. In our case, in Model-A, and according to the training dataset, the FP variable came first in the model's variables' average weight, relegating variables such as age or days of psycholeptics treatment–referred to in the prior literature (Deandrea et al., 2013; Aryee et al., 2017, Nakai et al., 2006, Callis 2016; Oliver et al., 2004;)– to second and third position, respectively. This fact would suggest that the inclusion of the FP variable may be a key factor in better discerning patients at risk. There are three possible interpretations. The variable could be either a mitigator (preventive care would be effective and reduce risk), or indicative of vulnerability (preventive care is provided to higher-risk patients according to expert criteria), or thirdly, a combination of both (Paxton et al., 2013; Cho et al., 2019). The rest of the variables in the model's configuration were sex (Callis 2016; Aryee et al., 2017; Anderson et al., 2015), incontinence (Callis 2016; Oliver et al., 2004), chronic obstructive pulmonary disease (Roig et al., 2011, Oliveira et al., 2020), family support (Lang 2014), diabetes (Yang et al. 2016), gait and treatment with different drugs (Callis 2016; Deandrea et al., 2013), all of which are repeatedly mentioned in a range of previous publications.

If we compare Model-A's results with that obtained in other studies in which AI were used, one could tentatively affirm (in the absence of knowledge of the IC for many of them) that it has a greater discriminant capacity than those previously obtained by Marschollek et al. (2012), Yokota et al. (2017), and that it presents similar results to that of Nakatani et al. (2019) and slightly worse than those obtained by Linderberg et al. (2020). The study by Cho et al. (2019) obtained a higher AUC (although the sensitivity and specificity values are not known), based on the information of the falls risk assessment used periodically by nurses. In the proposed model, the traditional instruments of falls risks or its individual items did not remain in the model, with the exception of "gait" item in the Downton instrument, completed exclusively at admission or when a patient's health status changes. This fact facilitates its application, since the model calculates the risk automatically and avoids the need to apply a risk monitoring instrument everyday manually, reducing the workload of the professionals.

Model-B, without FP variable, was a good and balanced model, better than Marschollek et al. (2012) and Yokota et al. (2017), but with less specificity than Model-A. However, its composition based on common variables and high availability in the EMR, facilitates the possibility that it can be used in contexts other than the original one.

Our study presents a number of limitations. First, some risk factors such as vestibular pathology (Khow et al., 2017) or arrhythmias (Evans et al., 2002), could not be included because they presented a high number of lost values. Second, although a great effort was made to recover all the falls during the study period, the retrospective design prevents guaranteeing their complete collection. Third, although the FP variable was incorporated in Model-A, the researchers could not analyse the related specific care received by patients, which makes this variable context dependent and hinders the exportability of the model. Fourth, it was possible to know the definitive model's average variable weights generated from the training dataset, but these weights were opaque for the researchers during the validation phase. Finally, the direction of the effect of the variables could not be obtained either.

Conclusions

Using AI techniques and including FP variable we have created a model to detect patients at risk of falling with good performance (Model-A). When comparing the model´s results without FP variable (Model-B) the model´s performance decreased. This latter model could be more easily exportable to other contexts by being made up of common and highly available variables in the EMR.

Implications for nursing management

We showed that the FP was a key variable to improve the model's performance. Currently, Model-A is integrated into the EMR and automatically provides a risk value several times a day (based on the patient's latest available clinical data) and its consultation has become part of the nurses' usual practice. It represents a decision-making support tool, that decrease nurses' workloads (they don't need to manually reassess the patient every day for risk of falls) and makes it possible to initiate preventive strategies in those who need it most. Model-A, useful in our context, might not be useful in others, given the specificity of the FP variable. However, we believe that Model-B, whose variables are highly available in the EMR, could be easily exportable to other contexts and facilitate nursing care. The major challenges that remain would be to evaluate the model's performance over time and analyse its predictive capacity in different environments or settings.

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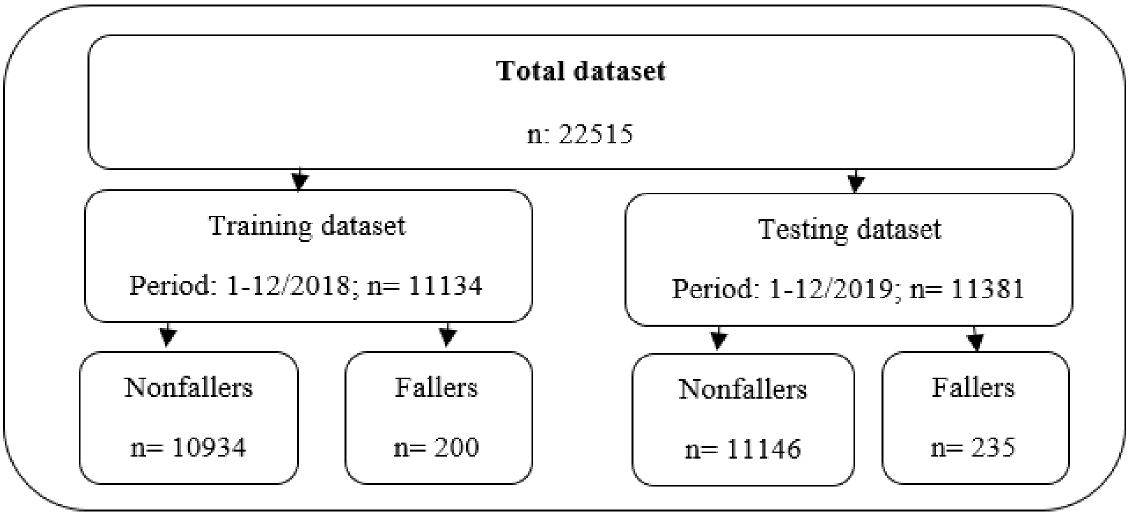


Figure 1. Dataset and design of the study

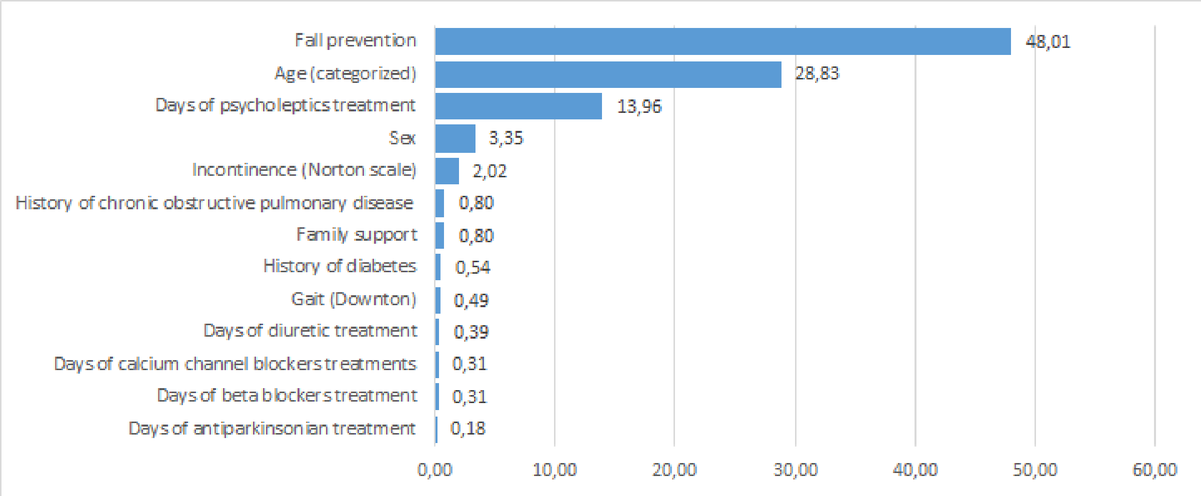


Figure 2. Relative weight distribution of Model A variables obtained from the training sample

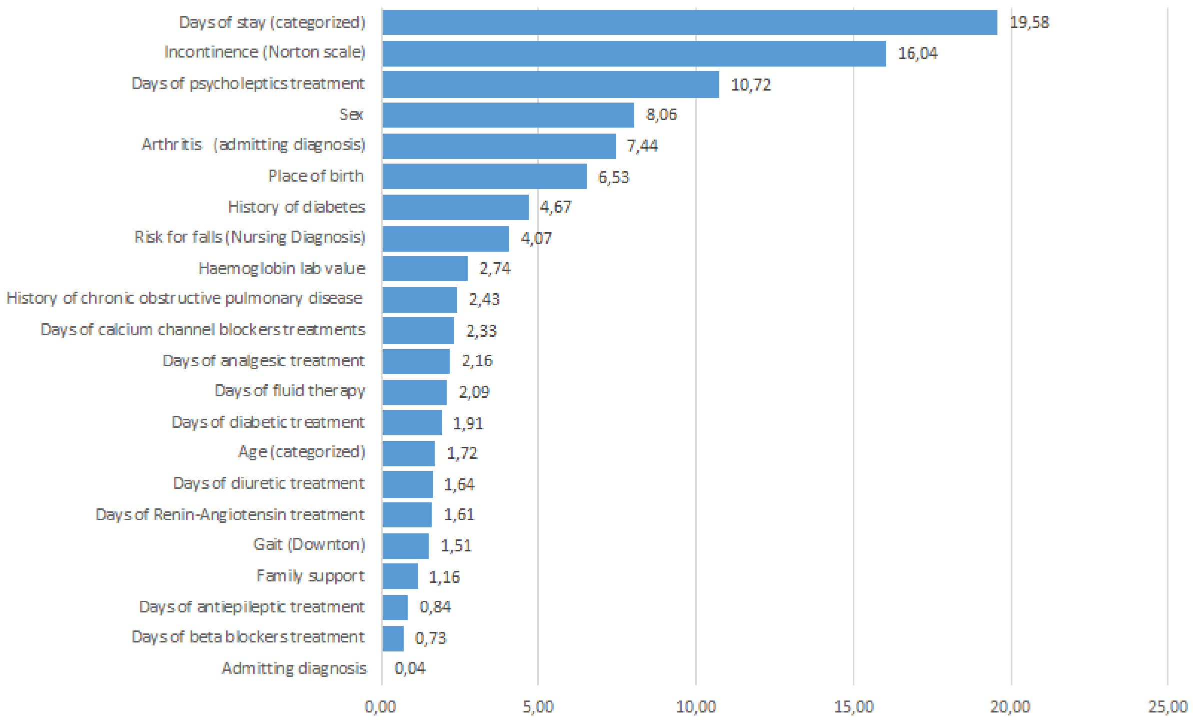


Figure 2. Relative weight distribution of Model B variables obtained from the training sample

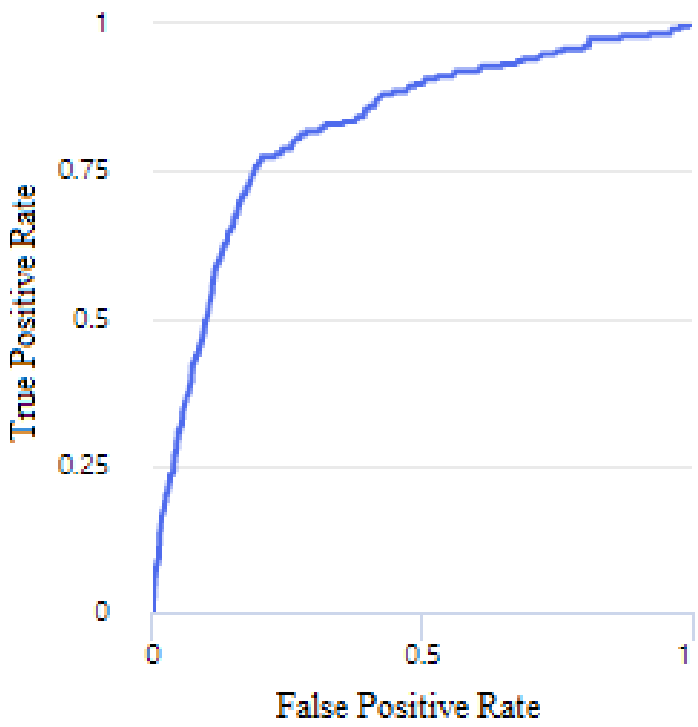
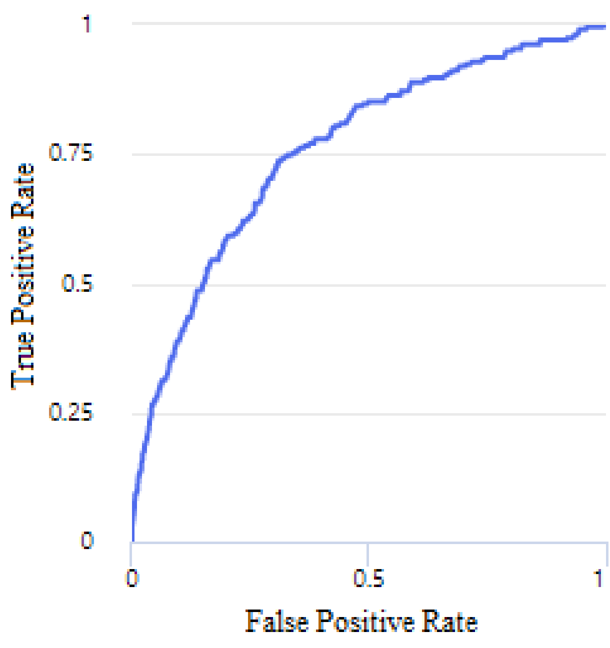


Figure 3. Receiver operator characteristic curves for the Two-Class Bayes Point Machine Model A (area under the curve [AUC], 0.82; 95% CI, 0.79-0.85).



Receiver operator characteristic curves for the Two-Class Bayes Point Machine Model B (area under the curve [AUC], 0.78; 95% CI, 0.74-0.82).

Table 1 Characteristics of patients

Variable		Total	%	2018 (Train)	%	2019 (Test)	%	Chi^2, t- Student or Comparison two population means	p value
Age (categorized)	16 - 59	4311	19.15	2109	18.94	2202	19.34		
	60 - 71	5024	22.32	2585	23.22	2439	21.43		
	72 - 80	6058	26.90	2981	26.77	3077	27.04		
	81 - 106	7122	31.63	3459	31.07	3663	32.19		
		22515	100.00	11134	100.00	11381	100.00	10.915	0.0122*
Sex	Male	12696	56.39	6339	56.93	6357	55.86		
	Female	9819	43.61	4795	43.07	5024	44.14		
		22515	100.00	11134	100.00	11381	100.00	1.07 (-0.22; 2.38)	0.106
Place of birth	Spain	15200	67.51	7493	67.30	7707	67.72		
	Outside Spain	7315	32.49	3641	32.70	3674	32.28		
		22515	100.00	11134	100.00	11381	100.00	-0.42 (-1.65; 0.81)	0.5104
Days of stay	1st Qu			3.00		3.00			
	Mean (SD)			7.10 (7.57)		7.28 (9.47)		-0.18 (-0.40; 0.05)	0.1173
	3rd Qu			8.00		8.00			
Previous falls in the hospital	Yes	609	2.70	289	2.59	320	2.81		
	No	21906	97.30	10845	97.41	11061	97.19		
		22515	100.00	11134	100.00	11381	100.00	-0.22 (-0.64; -0.23)	0.338
Previous falls (Downton scale)	Yes	1469	6.54	702	6.31	767	6.74		
	No	21046	93.46	10432	93.69	10614	93.26		
		22515	100.00	11134	100.00	11381	100.00	-0.43 (-1.09; 0.22)	0.1963
Downton total result (Downton scale)	Basic risk	10523	46.74	5274	47.37	5249	46.12		
	High risk	11992	53.26	5860	52.63	6132	53.88		

		22515	100.00	11134	100.00	11381	100.00	1.25 (-0.06; 2.56)	0.0625
History of stroke	Yes	5742	31.93	2755	24.74	2987	26.25		
	No	16773	68.07	8379	75.26	8394	73.75		
		22515	100.00	11134	100.00	11381	100.00	-1.51 (-2.65; -0.35)	0.0102*
History of diabetes	Yes	6156	27.34	3142	28.22	3014	26.48		
	No	16359	72.66	7992	71.78	8367	73.52		
		22515	100.00	11134	100.00	11381	100.00	1.74 (0.56; 2.91)	0.0036*
History of chronic obstructive pulmonary disease	Yes	7189	31.93	3538	31.78	3651	32.08		
	No	15326	68.07	7596	68.22	7730	67.92		
		22515	100.00	11134	100.00	11381	100.00	-0.48 (-0.4894; -0.4772)	0.6289
History of congestive heart failure	Yes	5919	26.09	2990	26.85	2929	25.74		
	No	16596	73.91	8144	73.15	8452	74.26		
		22515	100.00	11134	100.00	11381	100.00	-0.76 (-0.04; 2.28)	0.0586
History of dementia	Yes	1634	7.07	787	7.20	847	7.44		
	No	20881	92.93	10347	92.80	10534	92.56		
		22515	100.00	11134	100.00	11381	100.00	-0.13 (-1.06; 0.31)	0.2913
History of peripheral arterial disease	Yes	2498	11.09	1231	11.06	1267	11.33		
	No	20017	88.91	9903	88.94	10114	88.67		
		22515	100.00	11134	100.00	11381	100.00	0.03 (-0.91; 0.75)	0.8719
History of chronic kidney disease	Yes	5073	22.53	2472	22.20	2601	22.85		
	No	17442	77.47	8662	77.80	8780	77.15		
		22515	100.00	11134	100.00	11381	100.00	0.33 (-1.75; 0.45)	0.2485

History of cancer	Yes	5308	23.58	2543	22.84	2765	24.29		
	No	17207	76.42	8591	77.16	8616	75.71		
		22515	100.00	11134	100.00	11381	100.00	-1.45 (-2.57; -0.34)	0.0106*
History of depression	Yes	2335	10.37	1151	10.34	1184	10.40		
	No	20180	89.63	9983	89.66	10197	89.60		
		22515	100.00	11134	100.00	11381	100.00	0.03 (-0.87; 0.74)	0.889
History of anemia	Yes	6522	28.97	3206	28.79	3316	29.14		
	No	15993	71.03	7928	71.21	8065	70.86		
		22515	100.00	11134	100.00	11381	100.00	0.18 (-1.54; 0.85)	0.5821
History of osteoporosis	Yes	1489	6.61	709	6.38	780	6.85		
	No	21026	93.39	10424	93.63	10601	93.15		
		22515	100.00	11134	100.00	11381	100.00	-0.47 (-1.14; 0.17)	0.1501
History of sarcopenia	Yes	161	0.71	74	0.66	87	0.76		
	No	22354	99.29	11059	99.33	11294	99.24		
		22515	100.00	11134	100.00	11381	100.00	-0.10 (-0.33; 0.13)	0.4182
History of Hematological disease	Yes	3476	15.44	1660	14.91	1816	15.96		
	No	19039	84.56	9474	85.09	9565	84.04		
		22515	100.00	11134	100.00	11381	100.00	-1.05 (-1.99; -0.09)	0.0311*
History of Parkinson	Yes	752	3.34	369	3.31	383	3.37		
	No	21763	96.66	10765	96.69	10998	96.63		
		22515	100.00	11134	100.00	11381	100.00	-0.06 (-0.53; 0.43)	0.8601
History of arthritis	Yes	1607	7.14	776	6.97	831	7.30		

	No	20908	92.86	10358	93.03	10550	92.70		
		22515	100.00	11134	100.00	11381	100.00	-0.33 (-1.01; 0.35)	0.3464
Lives alone	Yes	1906	8.47	978	8.78	928	8.15		
	No	19266	85.57	9492	85.26	9774	85.88		
	Not applicable	1343	5.96	664	5.96	679	5.97		
		22515	100.00	11134	100.00	11381	100.00	2.905	0.234
Family support	Yes	18961	84.21	9272	83.28	9689	85.13		
	No	2384	10.59	1285	11.54	1099	9.66		
	Not applicable	1170	5.20	577	5.18	593	5.21		
		22515	100.00	11134	100.00	11381	100.00	21.023	0.0001*
Fall prevention	Yes	5544	24.62	2999	26.93	2525	22.19		
	No	16971	75.38	8135	73.07	8856	77.64		
		22515	100.00	11134	100.00	11381	100.00	4.75 (3.62; 5.88)	<0.0001*
Risk for falls (Nursing Diagnosis)	Yes	6571	29.18	3468	31.15	3102	27.26		
	No	15945	70.82	7666	68.85	8279	72.74		
		22515	100.00	11134	100.00	11381	100.00	3.89 (0.0269; 0.0509)	<0.0001*
Gait (Downton)	Yes	11075	49.18	5521	49.59	5554	48.80		
	No	11440	50.82	5613	50.41	5827	51.20		
		22515	100.00	11134	100.00	11381	100.00	0.79 (-0.53; 2.10)	0.2434
Days of diuretic treatment	1st Qu			0.00		0.00			
	Mean (SD)			3.21(5.29)		3.21 (5.82)		0.003 (-0.14; 0.15)	0.9642
	3rd Qu			5.00		5.00			
	1st Qu			10.4		10.50			

Haemoglobin lab value	Mean (SD)	11.83 (2.01)	11.85 (2.01)	-0.02 (-0.08; 0.03)	0.338 2
	3rd Qu	13.20	13.20		

*$p < 0.05$

Table 2 Performance of the different predictive classification models

Algorithm	Accuracy	Precision	Recall	F-Score	AUC
PCA - Based anomaly detection	0.5865	0.0533	0.6401	0.0984	0.6646
Averaged Perceptron	0.9665	0.6909	0.0918	0.1620	0.8089
Bayes Point Machine	0.9666	0.6618	0.1087	0.1867	0.8287
Boosted Decision Tree	0.9641	0.3939	0.0314	0.0582	0.8126
Decision Forest	0.9647	0.0000	0.0000	0.0000	0.8447
Decision Jungle	0.9647	0.0000	0.0000	0.0000	0.8226
Locally - Deep Support Vector Machine	0.9638	0.4724	0.2271	0.3067	0.7786
Logistic Regression	0.9666	0.7037	0.0918	0.1624	0.8263
Neural Network	0.9657	0.6571	0.0556	0.1025	0.8133
Support Vector Machine	0.9661	0.6818	0.0725	0.1310	0.7985

Table 3 Results of Model A and Model B

	Model A		Model B	
	Value	**Confidence interval**	**Value**	**Confidence interval**
Sensitivity	0.74	0.68-0.79	0.71	0.65-0.78
Specificity	0.82	0.81-0.83	0.74	0.73-0.75
F1-score	0.14		0.09	
Youden Index	0.55		0.45	
AUC	0.82	0.79-0.85	0.78	0.74-0.82