Fall risk prediction and validation in older adults

Leveraging electronic health records with machine learning

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Chapter

5

Development and internal validation of a prediction model for falls using electronic health records in a hospital setting

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Abstract

Objective

Fall prevention is important in many hospitals. Current fall-risk-screening tools have limited predictive accuracy specifically for older inpatients. Their administration can be time-consuming. A reliable and easy-to-administer tool is desirable to identify older inpatients at higher fall risk. We aimed to develop and internally validate a prognostic prediction model for inpatient falls for older patients.

Design

Retrospective analysis of a large cohort drawn from hospital electronic health record data.

Setting and Participants

Older patients (≥70 years) admitted to a university medical center (2016 until 2021).

Methods

The outcome was an inpatient fall (≥24 hours of admission). Two prediction models were developed using regularized logistic regression in 5 imputed datasets: one model without predictors indicating missing values (Model-without) and one model with these additional predictors indicating missing values (Model-with). We internally validated our whole model development strategy using 10-fold stratified cross-validation. The models were evaluated using discrimination (area under the receiver operating curve) and calibration (plot assessment). We determined whether the AUCs of the models were significantly different using DeLong test.

Results

Our dataset included 21,286 admissions. In total, 470 (2.2%) had a fall after 24 hours of admission. The Model-without had 12 predictors and Model-with 13, of which four were indicators of missing values. The AUCs of the Model-without and Model-with were 0.676 (95% CI: 0.646-0.707) and 0.695 (95% CI: 0.667-0.724). The AUCs between both models were significantly different (p=0.013). Calibration was good for both models.

Conclusions and implications

Both the Model-with and Model-without indicators of missing values showed good calibration and fair discrimination, where the Model-with performed better. Our models showed competitive performance to well-established fall-risk-screening tools, and they have the advantage of being based on routinely-collected data. This may substantially reduce the burden on nurses, compared to non-automatic fall-risk-screening tools.

Introduction

Falling during hospitalization is a serious complication (1). Especially for older patients, falls during hospital stay are common, occurring in approximately 6% of patients (2). Falls can lead to (severe) injuries, prolonged length of stay and higher costs (3, 4). Therefore, in many hospitals fall prevention is an important safety goal and each patient is screened for the individual fall risk, preferably within the first 24 hours after admission. Based on the individual fall risk, an assessment and the corresponding interventions are initiated with the goal of preventing inpatient falls is the recommended approach (5). An accurate tool to screen individual fall risks is therefore important as part of the fall prevention strategy.

There is a multitude of fall-risk-screening tools to identify hospitalized patients at higher fall risk. Examples of these tools include the John Hopkins Fall Risk Assessment Tool (JHFRAT) (6), Hendrich Fall Risk Model II (7), and STRATIFY (8). However, according to two systematic reviews, these tools have limited predictive accuracy specifically for older patients, rendering them unreliable for the prediction of inpatient falls in clinical practice (9, 10). Furthermore, the administration of these tools may impose a burden on staff, patients and healthcare professionals as it may demand additional data and rigorous examinations, and as a result might be also time-consuming. Therefore, a reliable and easy to administrate tool is desired to identify hospitalized older people at higher fall risk.

The amount of data captured in the Electronic Health Records (EHR) during the routine medical care is rapidly growing. Risk factors for inpatient falls have been explored in several studies and systematic reviews and include advanced age, fall history, impaired mental status, impaired mobility, dizziness, general weakness, prescribed medications and clinical diagnoses (11–14). EHR data contain a wide range of routinely-collected information including fall risk factors and thus offer a unique opportunity to develop prediction models for inpatient falls (15). An advantage of using a prediction model derived from EHR data is that this model relies on routinely-collected and readily available variables which can be retrieved and implemented in a clinical decision support system as a tool (16). As such, this tool has the potential to decrease the burden faced by healthcare professionals, support a more efficient work process, and can thereby improve patient fall risk identification.

Several studies used routinely-collected data extracted from hospital EHRs to develop or validate prediction models for inpatient falls (15, 17). However, these studies were conducted on populations with relatively young or middle-aged adults and not specifically older adults. These results may thus not generalize to older patients as cognitive decline, multimorbidity and polypharmacy may influence fall risk estimation. Another study reported on the development of two models to predict inpatient falls using EHR data collected in a geriatric hospital (18). However, these two models had poor predic-

tive ability and relied primarily on predictors related to physical and cognitive function. Whereas physical and cognitive impairment are important risk factors for inpatient falls, other risk factors that naturally exist in EHR data such as comorbidities, medication use, vital signs, laboratory results and clinical unit types remain underexplored and provide an opportunity to improve the predictive performance (19).

Therefore, the aim of this study was to develop and internally validate a prognostic prediction model for inpatient falls for older people using EHR data of a large hospital.

Methods

Study design, source of data and study population

This is a retrospective analysis of EHR data pertaining to older patients admitted to the [details omitted for double-anonymized peer review], an academic tertiary care hospital with 1,002 beds in [details omitted for double-anonymized peer review]. We included all admissions with a minimal length of stay of 24 hours (between January 2016 and January 2021) of patients aged 70 or over who did not experience falls during the first 24 hours of admission. The age criterion was selected in accordance with the guideline of the Dutch National Safety Program for hospitalized older patients (20), which was often applied in previous studies for Dutch older inpatients (21–23).

The study plan was reviewed by the [details omitted for double-anonymized peer review] which decided that the Medical Research Involving Human Subjects Act (WMO) does not apply.

Outcome

The outcome was the occurrence of any inpatient fall after 24 hours of hospital admission and during the hospital stay, regardless whether the patient fell multiple times or not. Falls were ascertained by text chart review of the problem list and the free text associated with each admission using a regular expression to search for fall and fall-related words (e.g., fall, fell, collapsed). A more detailed description on the definition and the determination of the outcome is published elsewhere (24).

Candidate predictors

The dataset underwent an inspection of potential predictors for inpatient falls based on literature, and clinical experience. These predictors included established fall risk factors as well as a wide variety of commonly collected data present in the EHR that may serve as proxies for risk factors of falls. For example, body temperature may be a surrogate for an infection which is known to be associated with inpatient falls. We included 66 potential predictors for inpatient falls (see Supplementary Table 1 for details). All

predictors were extracted only from data within the first 24 hours of admission. These predictors can be classified into 7 categories: (1) Demographic predictors including age and sex; (2) Healthcare utilization predictors including 24 admission departments and history of hospital admission; (3) Physiologic predictors: systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse, body temperature, pulse-oximetry, and body mass index (BMI); (4) Biochemical predictors: serum sodium, potassium, calcium, estimated glomerular filtration rate (eGFR), partial pressure of oxygen (PaO2) and partial pressure of carbon dioxide (PaCO2); (5) Comorbidity predictors: we constructed a comorbidity profile for each admission by aggregating the International Classification of Diseases tenth revision (ICD-10) coded diagnoses into 31 categories using Elixhauser comorbidity categories via the comorbidity package in R (25). In addition, we added the total number of the comorbidities as a predictor; (6) Medication predictors: we used 13 classes of medications based on the STOPPFall criteria (26) to group the medications which were coded using the Anatomical Therapeutic Chemical (ATC) (27) classification system. Furthermore, the total STOPPFall score was added. Information on the classes of the medications and the ATC codes used for grouping is given in Supplementary Table 2; and (7) Patient risk assessment scores: the score of the Short Nutritional Assessment Questionnaire (SNAQ) (28), Delirium Observation Screening (DOS) Scale (29), Katz Index of Independence in Activities of Daily Living (Katz ADL) (30). Moreover, we added "fall history", obtained from the JHFRAT, as a potential predictor. Fall history is an important risk factor for subsequent falls and many guidelines for fall prevention recommended the use of fall history as a starting point for fall risk stratification (31), including the recently published World Falls Guideline (5). We did not include the other JHFRAT variables as we aimed to develop a risk model with predictors requiring no or limited burden for nurses to record them.

Age, physiologic predictors, biochemical predictors (except eGFR), patient risk assessment scores and total Elixhauser comorbidities were kept as continuous variables and modelled without transformation. In case of multiple measurements, the mean value was used. eGFR values were not recorded as continuous for many patients (e.g., <60 or >90), and therefore, the first eGFR value was dichotomized into decreased eGFR (<60 ml/min per 1.73 m2) or normal eGFR (≥60 ml/min per 1.73 m2). Admission departments with less than 50 observations were merged into "other departments" category to avoid convergence issues during imputation of missing values. The rest of the predictors were dichotomous predictors. Interaction terms were not considered in this analysis.

Missing data

We considered all the predictors in the analysis regardless of the proportion of the missing values. We used the multiple imputation by chained equations procedure as implemented by the mice package in R (32). We generated five imputation sets using a max-

imum of five iterations for each imputation. The appropriate set of variables to impute each missing predictor was determined with the help of the quick selection option provided by the package.

Previous studies have demonstrated that the absence or presence of a particular measurement value might be informative and can be exploited in predictive modelling to improve the accuracy (33). For this reason, we augmented each predictor with missing values with a predictor indicating missing values. The value of this indicator was binary: 1 when the corresponding predictor value is missing, and 0 otherwise.

Model development and validation

We developed two logistic regression prediction models for inpatient falls. The first model utilized all the predictors without indicators for missing values (Model-without), and the second model combined both the potential predictors with the indicators (Model-with).

Our strategy to develop the abovementioned prediction models went through four steps: (1) generating five imputed datasets as described above; (2) variable selection in each imputed dataset, using regularized logistic regression with the least absolute shrinkage and selection operator (Lasso) as implemented by the glmnet package in R (34); (3) fitting unregularized logistic regression model on each of the five imputed datasets to predict inpatient falls based on variable retained in all imputed datasets; and (4) pooling the coefficients of these five models to obtain a final prediction model.

We internally validated our model development strategy using 10-fold stratified cross-validation. The entire strategy (including multiple imputation and tuning the lambda hyperparameter for Lasso) was repeated in each of the 10 folds on the training set (90% of the data) and tested on the held-out test set (10% of the data).

Model performance

The performance of the two models was evaluated with measures of discrimination, using the area under the receiver operating curve (AUC), and calibration, by visual inspection of loess-smoothed calibration plots (35). We calculated the mean and the 95% confidence interval (CI) of the AUC of the pooled prediction model across the 10 folds. The DeLong test was used to determine whether the differences in the AUCs between the two models, with and without indicators for missing values, are statistically significant (36).

Statistical analysis was performed using the R statistical software environment version 4.0 (R Foundation for Statistical Computing, Vienna, Austria). This study is reported in accordance with the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis statement (TRIPOD) (37).

Sensitivity analysis

As mentioned before, we excluded patients who endured falls in the first 24 hours of admission. To assess the robustness of the prediction models, we performed a sensitivity analysis to evaluate the impact of adding these patients on the predictive performance of the best performing model.

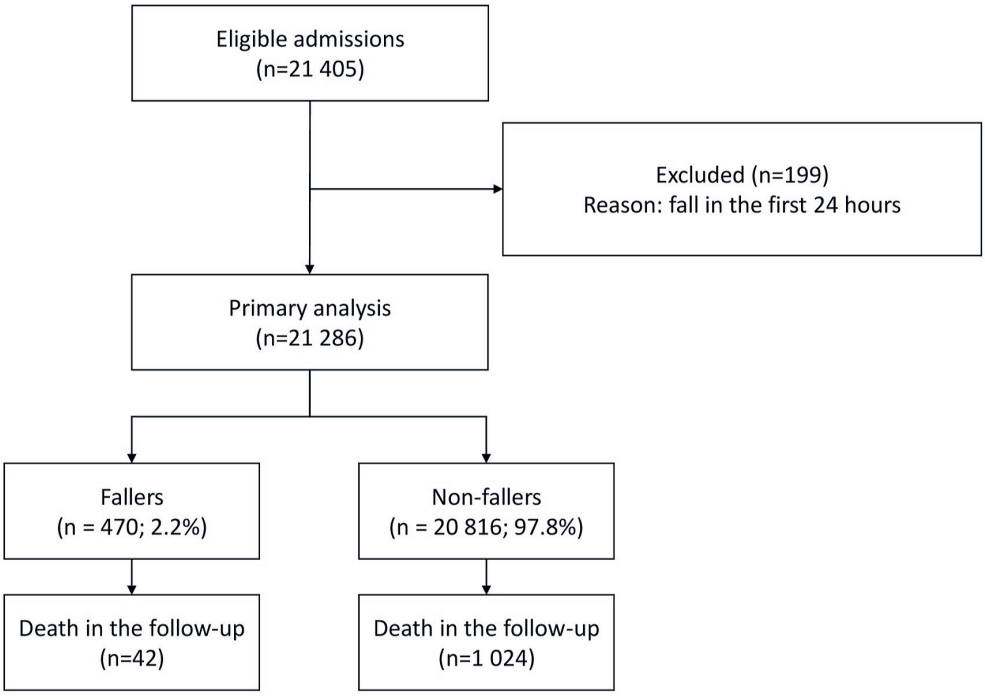

Figure 1: The flow of the participants throughout the study.

Results

Study population

The flow of the participants throughout this study is shown in Figure 1. In total, 21,405 eligible admissions were identified during the study period. Admissions with falls in the first 24 hours (n=199) were excluded leaving 21,286 admissions to be included in the final analysis for model development. The prevalence of falls after 24 hours of admission was 2.2% (n=470). Table 1 describes the baseline characteristics of the study population. The median age was fairly similar for both fallers and non-fallers (77 vs 76 years). Fallers were generally male individuals (57% vs 52.9%), had a longer length of stay (median days 15.6 vs 3.96) and had more often been previously admitted to the hospital (41.5% vs 33.6%). In addition, the mean score of DOS, Katz ADL and SNAQ was higher

in fallers compared with non-fallers, (2.06; SD=2.67 vs 1.10; SD=2.00), (2.25; SD=2.35 vs 1.08; SD=1.88), and (1.30; SD=1.80 vs 0.794; SD=1.48), respectively. A complete list of baseline characteristics is available in Supplementary Table 3.

Table 1: Baseline Characteristics of the Study Participants

Predictor	Nonfallers (n = 20,816)		Fallers (n = 470)	
	Value	Missing n (%)	Value	Missing n (%)
Age, median (IQR)	76.0 (72.0, 81.0)	—	77.0 (77.0, 82.0)	—
Female sex	9,809 (47.1)	—	202 (43.0)	—
Length of stay, d, median (IQR)	3.96 (1.94, 7.83)	—	15.6 (8.79, 28.9)	—
Previous admission	6,992 (33.6)	—	195 (41.5)	—
Fall history	3,328 (16.0)	5,174 (24.9)	129 (27.4)	152 (32.3)
BMI, mean (SD)	26.3 (4.95)	12,230 (58.8)	25.9 (4.69)	267 (56.8)
STOPPFall score, mean (SD)	1.37 (1.12)	—	1.45 (1.11)	—
Elixhauser score, mean (SD)	1.04 (1.50)	—	1.41 (1.63)	—
DOS score, mean (SD)	1.10 (2.00)	16,467 (79.1)	2.06 (2.67)	300 (63.8)
Katz ADL score, mean (SD)	1.08 (1.88)	5,543 (26.6)	2.25 (2.35)	161 (34.3)
SNAQ score, mean (SD)	0.794 (1.48)	6,107 (29.3)	1.30 (1.80)	183 (38.9)
Decreased eGFR	6,642 (31.9)	6,581 (31.6)	210 (44.7)	80 (17.0)
Serum potassium, mmol/L, mean (SD)	4.21 (0.73)	7,733 (37.1)	4.22 (0.65)	94 (20.0)
<3.5	959 (4.6)	—	26 (5.5)	—
3.5-5.0	11,184 (53.7)	—	310 (66.0)	—
>5.0	940 (4.5)	—	40 (8.5)	—
Serum sodium, mmol/L, mean (SD)	137 (5.04)	7,690 (36.9)	137 (5.23)	94 (20.0)
<135	2,918 (14.0)	—	115 (24.5)	—
135-145	10,048 (48.3)	—	249 (53.0)	—
>145	160 (0.8)	—	12 (2.6)	—
Serum calcium, mmol/L, mean (SD)	2.24 (0.228)	17,374 (83.5)	2.24 (0.311)	327 (69.6)
<2.1	765 (3.7)	—	30 (6.4)	—
2.1-2.65	2,595 (12.5)	—	107 (22.8)	—
>2.65	82 (0.4)	—	6 (1.3)	—
Pao2, mm Hg, mean (SD)	14.8 (9.49)	16,236 (78.0)	13.6 (8.35)	299 (63.6)
Paco2, mm Hg, mean (SD)	5.26 (1.25)	16,241 (78.0)	5.18 (1.07)	298 (63.4)
SBP, mm Hg, mean (SD)	131 (21.3)	219 (1.1)	130 (22.8)	3 (0.6)
DBP, mm Hg, mean (SD)	68.6 (12.5)	219 (1.1)	68.8 (13.5)	3 (0.6)
Heart rate, bpm, mean (SD)	75.3 (15.2)	214 (1.0)	79.8 (16.0)	3 (0.6)
Pulse oximetry, %, mean (SD)	97.0 (2.56)	1,219 (5.9)	96.7 (2.37)	35 (7.4)
Body temperature, °C, mean (SD)	36.7 (0.722)	529 (2.5)	36.7 (0.712)	5 (1.1)

continued

Table 1: Baseline Characteristics of the Study Participants

Predictor	Nonfallers (n = 20,816)		Fallers (n = 470)	
	Value	Missing n (%)	Value	Missing n (%)

Notes: BMI, body mass index; bpm, beats per minute; DBP, diastolic blood pressure; DOS, Delirium Observation Screening; Katz ADL, Katz Index of Independence in Activities of Daily Living; Paco2, partial pressure of carbon dioxide; Pao2, partial pressure of oxygen; SBP, systolic blood pressure; SNAQ, Short Nutritional Assessment Questionnaire.

Unless otherwise specified data are presented as n (%).

Missing data

Missing values were observed in 16 predictors and the range of missingness was between 1.0% and 83.2%. As a result, 16 indicators for missing values were added as predictors in the Model-with model. Supplementary Table 4 lists the predictors with missing values and the proportion of missingness.

Model development and specification

Table 2 and table 3 show the predictors of the final prediction models. The number of predictors in Model-without was 12 whereas Model-with had 13, of which four were missing indicators.

Table 2: The Final Prediction Model for Inpatient Falls as Derived From the Data Without Indicators for Missing Values

Predictor	Coefficient	OR (95% CI)	*P* value
Intercept	−5.19*		
JHFRAT: fall history	0.35	1.42 (1.08-1.88)	.015
Elixhauser: congestive heart failure	0.25	1.28 (0.91-1.82)	.15
Elixhauser: cardiac arrhythmias	0.27	1.31 (0.98-1.75)	.06
Elixhauser: renal failure	0.30	1.35 (0.96-1.90)	.08
Elixhauser score	0.03	1.03 (0.95-1.11)	.48
STOPPFall-antipsychotics	0.63	1.88 (1.31-2.68)	<.001
Admission to neurologic department	0.53	1.70 (1.27-2.26)	<.001
Admission to emergency department	0.67	1.95 (1.46-2.63)	<.001
Admission to women's diseases department	−1.60	0.20 (0.08-0.54)	.002
Heart rate	0.01	1.01 (1.00-1.02)	.002
Katz ADL score	0.09	1.09 (1.04-1.16)	.002
DOS score	0.05	1.05 (0.99-1.11)	.11

continued

Table 2: The Final Prediction Model for Inpatient Falls as Derived From the Data Without Indicators for Missing Values

Predictor	Coefficient	OR (95% CI)	*P* value

Notes: DOS, Delirium Observation Screening; Katz ADL, Katz Index of Independence in Activities of Daily Living; OR, odds ratio.

Numbers are rounded to 2 decimal places.

Inpatient fall probability can be calculated for this model using the formula 11+e−LP, where LP (linear predictor) is equal to −5.19 + (0.35 × JHFRAT fall history) + (0.25 × Elixhauser congestive heart failure) + (0.27 × Elixhauser cardiac arrhythmias) + (0.30 × Elixhauser renal failure) + (0.03 × Elixhauser score) + (0.63 × STOPPFall antipsychotics) + (0.53 × Admission to neurologic department) + (0.67 × Admission to emergency department) + (−1.60 × Admission to women's diseases department) + (0.01 × Heart rate) + (0.09 × Katz ADL score) + (0.05 × DOS score).

The 95% CI of the intercept's coefficient is −5.49 to −4.57.

Table 3: The Final Prediction Model for Inpatient Falls as Derived From the Data With Indicators for Missing Values

Predictor	Coefficient	OR (95% CI)	*P* value
Intercept	−3.95*		
JHFRAT: fall history	0.34	1.40 (1.06-1.87)	.019
Elixhauser: cardiac arrhythmias	0.35	1.42 (1.11-1.81)	.005
Elixhauser: renal failure	0.33	1.39 (1.04-1.86)	.024
STOPPFall-antipsychotics	0.48	1.62 (1.14-2.31)	.007
Admission to neurologic department	0.53	1.70 (1.27-2.28)	<.001
Admission to emergency department	0.56	1.75 (1.30-2.36)	<.001
Heart rate	0.01	1.01 (1.00-1.01)	.026
Katz ADL score	0.06	1.06 (1.00-1.13)	.06
DOS score	0.04	1.04 (0.98-1.11)	.15
Missing potassium	−0.38	0.68 (0.53-0.88)	.003
Missing calcium	−0.25	0.78 (0.62-0.98)	.031
Missing Paco2	−0.32	0.73 (0.58-0.90)	.004

Missing DOS score	−0.41	0.66 (0.53-0.83)	<.001

Notes: DOS, Delirium Observation Screening; Katz ADL, Katz Index of Independence in Activities of Daily Living; OR, odds ratio.

Numbers are rounded to 2 decimal places.

Inpatient fall probability can be calculated for this model using the formula 11+e−LP, where LP (linear predictor) is equal to −3.95 + (0.34 × JHFRAT fall history) + (0.35 × Elixhauser cardiac arrhythmias) + (0.33 × Elixhauser renal failure) + (0.48 × STOPPFall antipsychotics) + (0.53 × Admission to neurologic department) + (0.56 × Admission to emergency department) + (0.01 × Heart rate) + (0.06 × Katz ADL score) + (0.04 × DOS score) + (−0.38 × Missing potassium) + (−0.25 × Missing calcium) + (−0.32 × Missing Paco2) + (−0.41 × Missing DOS score).

* The 95% CI of the intercept's coefficient is −4.50 to −3.39.

Model performance

The discrimination ability of the Model-without and Model-with, as measured with the AUC, was 0.676 (95% CI: 0.646-0.707) and 0.695 (95% CI: 0.667-0.724), respectively. The difference between the AUCs of both models was statistically significant (p=0.013). With respect to calibration, both models showed similar good performance as depicted in figure 2.

Sensitivity analysis

The AUC of the Model-with, when we included the patients who fell in the 24 hours after admission was 0.696 (95% CI: 0.675-0.717). The inclusion of these patients showed comparable calibration plots to Model-with (see Supplementary Figure 1).

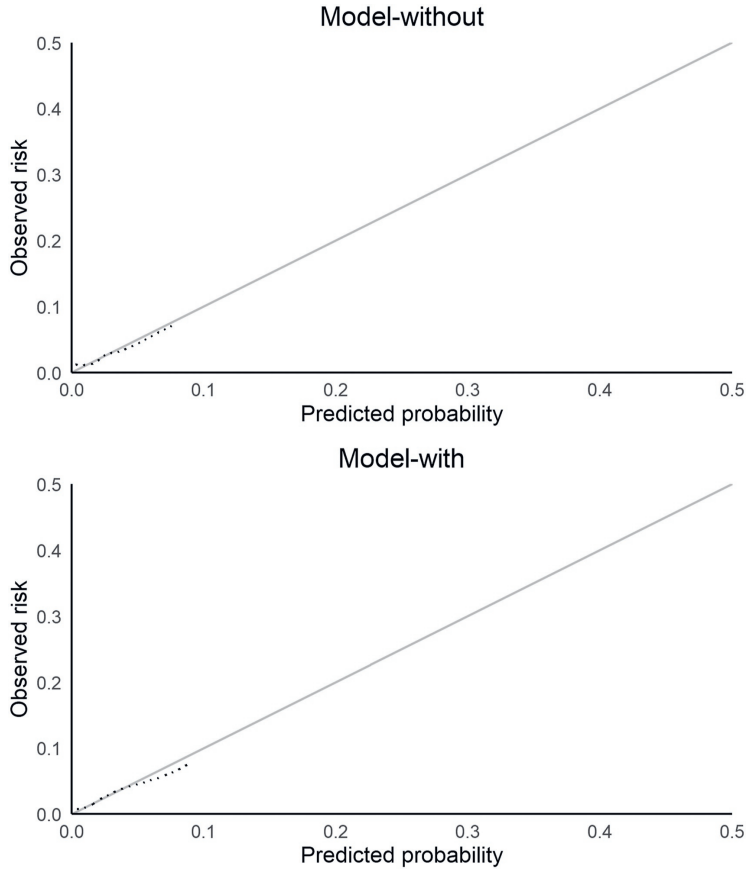

Figure 2: The calibration plots of the prediction models of inpatient falls. Calibration plots are shown for the model derived without using indicators for missing values (Model-without) and the model using indicators for missing values (Model-with). Calibration plots demonstrate the relation between the predicted and observed fall risk. The diagonal line represents perfect calibration. The dotted line reflects actual model calibration. Points under the diagonal line reflect over prediction, whereas points above the diagonal line reflect under prediction. Only probabilities between the 2.5th and 97.5th percentiles are shown.

Discussion

In this study, we developed and internally validated two prediction models for inpatient falls using routinely-collected hospital EHR data. Both models, one with and one without indicators for missing values as predictors, demonstrated fair discrimination performance, where the model with the indicators had superior performance. Both models showed good calibration.

The major strength of our study is the large sample size of older adults from a representative proportion of persons aged≥70 years. Additionally, we explored the predictive merit of many predictors such as medications, morbidities, lab measurements and vital signs, which were underexplored in the literature. Moreover, we used cross-validation to internally validate the models, the recommended method of multiple imputation to handle missing data in order to avoid potential bias,(37) sensitivity analysis to ensure the robustness of the models and reported on both discrimination and calibration. The discriminative ability of our models as measured with the AUC falls near the upper range of the AUCs of the JHFRAT (0.58 to 0.71) reported in several studies (38–40), including a validation study using the same data as in this study (41). The JHFRAT is based on expert knowledge and literature and it is often administered by well-trained nurses who are required to complete many other risk assessments throughout the patients' admissions, besides performing other nursing care activities. This makes this task not only time-consuming but also increases the burden of documentation on nurses. By contrast, our models do not require additional data collection as they rely on routinely-collected variables which are readily available in hospital EHR except for the variable previous fall.

Compared to previously developed prediction models for inpatient falls using EHR data, the discrimination of our models exceeded that of the one obtained by (18) who reported an AUC of 0.63 in a geriatric hospital setting. A possible explanation of this difference is the fact that our models contained more predictors which were broad in scope addressing other fall risk aspects such as the existence of comorbidities and using certain medications. On the other hand, our models performed less well in terms of discrimination compared to the studies which considered the general adult population, where the AUC ranged between 0.82 and 0.90 (15, 42, 43). However, fall risk prediction for geriatric inpatients is challenging as they are a heterogeneous group with high level of comorbidities and polypharmacy, limiting discrimination capacity. Like in the study by (42) and unlike the abovementioned studies, we assessed model calibration.

Our final model without using indicators for missing variables identified 12 predictors as harbingers of inpatient falls. Among these predictors, fall history, use of antipsychotic medications, functional limitations and confused mental status are widely recognized in the literature as risk factors for inpatient falls (11, 12, 44). Similarly, patients with cardiovascular diseases, namely, heart failure and cardiac arrhythmias, were more likely to fall due to various reasons, including, among others, medication use. In-hospital

medication reviews by clinicians are therefore imperative to decrease fall risk (45). Impaired renal function was also retained in our final model. As our hospital is a university medical center including specific sub-specialty care, patients were more likely to have severe renal impairment or to receive hemodialysis in our study sample. Older adults undergoing hemodialysis have been reported to be at higher fall risk (46). Admission to certain units such as the emergency and neurological units was found to be a strong predictor for inpatient falls, corroborating findings from previous studies which utilized EHR data to develop prediction models for inpatient falls (15, 42).

The results of this study showed that the inclusion of indicators of missing values improves the predictive performance. These indicators may have served as surrogates for latent information. For example, a missing serum potassium measurement (retained in our second model) may be associated with unmeasured variables related to kidney or heart diseases, or condition treated with diuretics or heart medications. The protective effect of the absence of the serum potassium measurement may suggest that the aforementioned conditions were deemed by the clinician to be irrelevant to the patient, and therefore, this patient is relatively healthy and may not fall. However, the improvement in the predictive performance does not imply clinical relevance and these results should be interpreted with caution as indicators of missing values have no specific clinical meaning but only a nonspecific one (47). In addition, the generalizability of prediction models derived by means of such indicators is limited as the underlying mechanism that produced the missing values may differ between settings and may change over time (33, 48). In any case, these models require continuous monitoring and revision when used in real practice (33).

An important limitation of this study is the incomplete registration of diagnoses in the first 24 hours of admission. This limitation is inherent in the policy and process of code registration in the hospital, or it can be that some diagnoses were not yet confirmed in the first 24 hours of admission. Nevertheless, our aim was to develop a prediction model based on what is available in the EHR to decrease documentation burden, mimicking the real practice situation. Another limitation is the exclusion of patients who fell within 24 hours of admission. The rationale behind this is that we used only predictors before fall events and within the first 24 hours, and thus it was uncertain whether the predictors were assessed before or after a fall for these patients. Nevertheless, our sensitivity analysis showed comparable results to that of the primary analysis when we included the falls within 24 hours of admission. Moreover, although our prediction models can be useful to identify older adults at higher fall risk, they can be only used to predict the first fall but not recurrent falls as recurrent fallers are more likely to have different clinical characteristics. Our dataset did not include recurrent fallers to investigate these potential differences. Furthermore, our results pertain to one academic hospital setting. The extent to which the results generalize to non-academic hospitals or other clinical settings

remains to be established, as other settings could have different case-mix (i.e. patient characteristics) or different EHR variables. For example, nursing homes and assisted living settings have different policy or protocols affecting which physiological and biochemical values are routinely collected. Future work is required to externally validate the models and to evaluate the reproducibility of our results in different related populations (e.g., academic/non-academic hospital settings) and the transportability to an unrelated population (e.g., post-acute or long-term care settings) (48). Finally, the number of fall events in the dataset was lower than would be expected for hospitalized older adults in other research cohort studies. It might be that not all falls were reported or documented in the EHR, and it is likely that only the serious falls were recorded. It could also be attributed to our search strategy to ascertain fall events, although we relied on two sources to detect falls (problem list and free text). Nevertheless, this limitation is acknowledged in other studies using EHRs to capture fall events (49, 50).

Conclusions and Implications

Healthcare organizations, seeking to promote work process efficiency and minimize redundant documentation, can consider the implementation of our prediction model, or its developmental strategy, into their existing fall prevention workflow to automatically generate a fall risk score based on routinely-collected data. This may substantially reduce the burden on nurses, compared to, for example, using the JHFRAT or any other non-automatic fall-risk-screening tool. Furthermore, our work facilitates the use of a decision support system built on top of our models because it can seamlessly be integrated in an EHR to automate fall risk prediction which would potentially free time for nurses to focus on other crucial activities.

Supplemental material

All supplemental material related to this chapter can be found in the online published article:
`https://www.jamda.com/article/S1525-8610(23)00285-2/fulltext`

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