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Original Study

Machine Learning Prediction for Postdischarge Falls in Older Adults: A Multicenter Prospective Study

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A B S T R A C T

Objectives: The study aimed to develop a machine learning (ML) model to predict early postdischarge falls in older adults using data that are easy to collect in acute care hospitals. This may reduce the burden imposed by complex measures on patients and health care staff.
Design: This prospective multicenter study included patients admitted to and discharged from geriatric wards at 3 university hospitals and 1 national medical center in Japan between October 2019 and July 2023.
Setting and Participants: The participants were individuals aged ≥65 years. Of the 1307 individuals enrolled during the study period, 684 were excluded, leaving 706 for inclusion in the analysis.
Methods: We extracted 19 variables from admission and discharge data, including physical, mental, psychological, and social aspects and in-hospital events, to assess the main outcome measure: falls occurring within 3 months postdischarge. We developed a prediction model using 4 major classifiers, Extra Trees, Bernoulli Naive Bayes, AdaBoost, and Random Forest, which were evaluated using a 5-fold cross-validation. The area under the receiver operating characteristic curve (AUC) was used to evaluate predictive performance.
Results: Among the 706 patients, 114 (16.1%) reported a fall within 3 months postdischarge. The Extra Trees classifier demonstrated the best predictive performance, with an AUC of 0.73 on the test data. Important features included the Lawton Instrumental Activities of Daily Living scale, Clinical Frailty Scale (≥4 points), presence of urinary incontinence, 15-item Geriatric Depression Scale (≥5 points), and preadmission residence, all assessed at admission.
Conclusions and Implications: To our knowledge, this is the first study to develop an ML model for predicting early postdischarge falls among older patients in acute care hospitals. The findings suggest that this model could assist in developing fall-prevention strategies to ensure seamless transition of care from hospitals to communities.

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Falls are a major public health problem, with approximately 30% of individuals aged ≥65 years experiencing falls annually.[1] Falls represent a leading cause of care dependency among older adults and significantly impact their quality of life.[2,3] The risk of falls increases significantly during the early postdischarge period, with the incidence of falls reported to be approximately 3 times higher than that before hospitalization.[4] This increase in adverse outcomes associated with hospitalization is referred to as hospital-associated disability (HAD) and is largely driven by the development of new activities of daily living (ADL) impairments and declines in physical and cognitive function resulting from prolonged bed rest during hospitalization.[5] HAD occurs in approximately 30% of hospitalized patients aged ≥65 years,[6] leading to postdischarge muscle weakness, balance disorders, and cognitive decline, which in turn increase the risk of further falls.[7,8]

Previous fall-prediction models have primarily focused on community-dwelling older adults and hospitalized patients. However, for patients in the early postdischarge period, it is essential to develop fall-prediction models that account for functional decline during hospitalization and changes in the postdischarge environment.

Fall risk factors are complex, and traditional statistical models are often limited by the number of confounding variables they can handle, making it difficult to build highly accurate prediction models. In contrast, machine learning (ML) is expected to be a more suitable method for developing accurate fall prediction models, as it can capture the complex interactions between multiple variables.

Recently, ML techniques have been employed to develop models with high predictive performance for falls. However, these models often include variables that require complex measurements, such as blood data, muscle strength, balance function, and gait speed.[9,10] These measurements can be burdensome for patients, require specialized skills, and are time-consuming for health care providers, making them difficult to obtain. Consequently, missing data may occur, which not only affects the performance of ML models but also hinders their widespread implementation across various health care settings.

The purpose of this study was to develop an ML model for predicting early postdischarge falls. This model uses information that could be easily obtained by health care providers in busy acute care hospitals while minimizing the burden on patients. This approach is expected to be an important step toward integrating hospital and community fall-prevention strategies, thereby enabling seamless fall-risk management for patients from hospitalization through to postdischarge.

Methods

Study Design

The data analyzed in this prospective cohort study were obtained from the Japan Hospital Acquired Complications study, an observational multicenter study that included the Nagoya University Hospital, the Osaka University Hospital, the University of Tokyo Hospital, and the National Center for Geriatrics and Gerontology in Japan.[11] We included patients admitted to and discharged from an acute geriatric ward at any of the 4 facilities between October 2019 and July 2023. The only inclusion criterion was aged ≥65 years. The exclusion criteria were hospitalization of ≤2 days, lack of consent, estimated life expectancy of <1 month according to the attending physician, readmission within 3 months of the last hospitalization, intrahospital transfer, and missing data on postdischarge falls.

The study protocol was approved by the Ethics Committee of each participating facility. Written informed consent was obtained from all participants after explaining the study details, including the 3-month postdischarge telephone survey. For patients with cognitive impairment, informed assent was obtained from patients and proxy consent from their family caregivers.

Definition of Falls and Early Postdischarge Period

Falls are defined as "events which results in a person coming to rest inadvertently on the ground or floor or other lower level."[12] Early postdischarge falls were defined as falls occurring within 3 months after discharge. This 3-month short-term follow-up period was selected based on previous studies focused on capturing the direct impact of HAD.[8,13] Three months after discharge, researchers contacted patients or their family caregivers by telephone to inquire about any falls that had occurred since discharge. During these interviews, we gathered detailed information on the participants' health status, activities of daily living, and living conditions, verifying fall occurrences through specific daily situations. For patients with cognitive decline, information was collected from family caregivers to enhance data reliability.

Data Collection and Variable Processing

We initially selected 38 variables based on previously reported fall risks and ease of data collection, using data from both admission and discharge. These variables were derived from standardized assessment items based on Comprehensive Geriatric Assessment, which is routinely conducted as part of daily clinical practice at the participating facilities. These assessment tools were not specifically added for research purposes but rather are established as standard clinical processes at each facility, and all data were collected from electronic medical records. Details of each variable are provided in Supplementary Tables 1 and 2.

Admission data included age; prehospital residence; family composition; current smoking status; body mass index; and the presence or absence of polypharmacy, sleep disorders, diarrhea, and urinary incontinence, among others. Physical function was assessed through various measures, including the Barthel Index (BI), Lawton Instrumental ADL (IADL) scale, and Clinical Frailty Scale (CFS).[14-17] Mental and psychological factors were evaluated using the Mini-Mental State Examination, the 15-item Geriatric Depression Scale (GDS-15), and other relevant measures.[18,19] Discharge data included changes in CFS scores from admission to discharge, falls during hospitalization, and the occurrence of delirium and newly acquired incontinence, among other factors. The presence of delirium during hospitalization was assessed by the attending physician using criteria from the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition*.[20]

During the preprocessing of the input variables, age was dichotomized using a cutoff of 75 years, as this threshold is considered clinically appropriate and supported by the literature, and was confirmed to optimize the performance of the predictive model.[21] Other continuous variables were dichotomized based on cutoff values established in previous studies (Supplementary Table 1).

Model Development Using Supervised ML

We developed a prediction model using 4 classifiers: Extra Trees, Bernoulli Naive Bayes, AdaBoost, and Random Forest. These models were chosen for their strong performance across multiple metrics [area under the receiver operating characteristic curve (AUC), accuracy, and balanced accuracy] and their proven effectiveness in handling complex data sets.[22,23] Extra Trees and Random Forest effectively handle high-dimensional data and prevent overfitting,[24] whereas Bernoulli Naive Bayes provides efficient, interpretable binary classification.[25] AdaBoost combines weak learners for accuracy.[26]

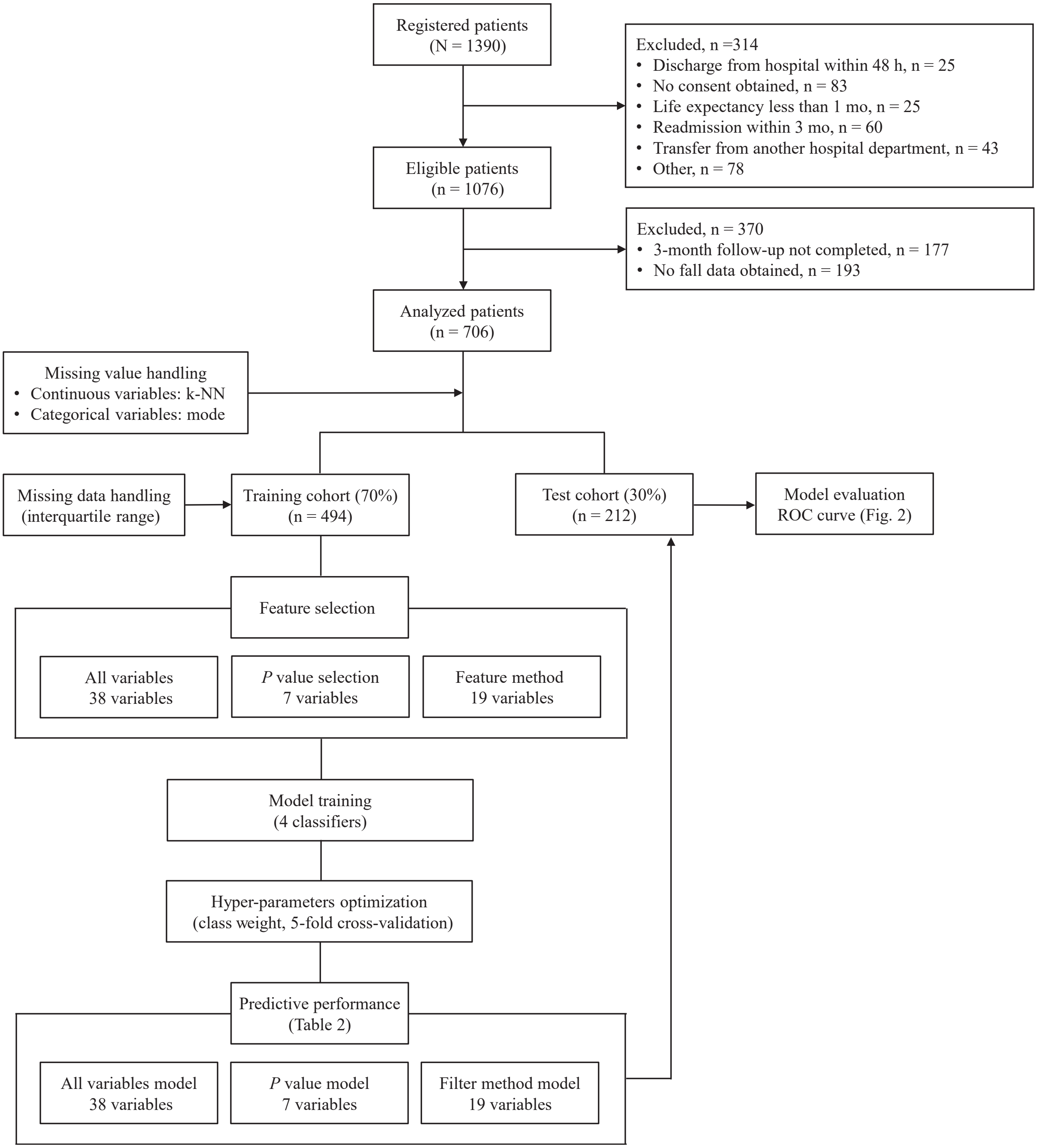

Fig. 1. Flow of the training and validation processes for early postdischarge fall prediction model. k-NN, k-nearest neighbors.

These ensemble methods enabled algorithmic comparison and complementary strengths.[27]

We developed and evaluated the model using the following approach (Figure 1). To handle missing values in the data set, we imputed continuous variables using k-nearest neighbors and categorical variables using the mode. Outliers in the training data were adjusted using the interquartile range method. Next, the data set was divided into training (70%) and test data (30%). Features were selected from the training data using the filter method (information gain >0). A grid search with 5-fold cross-validation was conducted to build the optimal model based on the selected features. Considering the data imbalance, class weights were applied during hyperparameter optimization to enhance model performance and ensure balanced accuracy was optimized. The model was trained on the training data using the optimized hyperparameters. The performance of this model was compared with a model using all 38 variables and a model using 7 variables that showed significance in conventional univariate analysis (Supplementary Table 2). Multicollinearity among features was evaluated using the variance inflation factor (Supplementary Table 3).

Table 1
Selected Features and Participant Characteristics by Postdischarge Fall Status

	Total (N = 706)	Nonfall Group (n = 592; 83.9)	Fall Group (n = 114; 16.1)	*P* Value*
Data at admission				
Age ≥75 y	645 (91.5)	537 (90.9)	108 (94.7)	.24
Prehospital residence (nonhome)	116 (16.5)	102 (17.3)	14 (12.4)	.25
Family composition (living alone)	147 (21.8)	125 (22.2)	22 (20.0)	.71
Smoking status (current)	25 (3.6)	19 (3.2)	6 (5.3)	.41
Obesity (BMI ≥ 25)	137 (19.9)	116 (20.0)	21 (18.9)	.89
Underweight (BMI < 18.5)	148 (21.6)	123 (21.4)	25 (22.7)	.85
Polypharmacy (≥5 medications)	5.8 ± 3.7	5.7 ± 3.6	6.5 ± 4.0	.05
Sleep disorder	206 (29.2)	170 (28.7)	36 (31.6)	.61
Diarrhea	18 (2.6)	16 (2.7)	2 (1.8)	.79
Urinary incontinence	364 (51.6)	285 (48.1)	79 (69.3)	<.001
Barthel Index score	73.3 ± 31.9	73.9 ± 32.5	70.0 ± 28.8	.20
Lawton IADL scale score	49.0 ± 40.5	51.6 ± 40.8	35.9 ± 36.0	<.001
Clinical Frailty Scale (≥4 points)	5.0 ± 1.7	4.9 ± 1.8	5.5 ± 1.3	<.001
Lower leg circumference (male < 34, female < 33), cm	30.3 ± 4.7	30.4 ± 4.8	29.7 ± 4.0	.12
GDS-15 (≥5 points)	4.9 ± 3.7	4.7 ± 3.6	6.0 ± 3.6	<.001
Data at discharge				
Clinical Frailty Scale score change	108 (15.7)	90 (15.6)	18 (16.4)	.95
Falls during hospitalization	45 (6.5)	33 (5.7)	12 (10.7)	.08
Delirium during hospitalization	97 (14.0)	75 (12.9)	22 (19.6)	.08
Newly acquired incontinence	12 (1.7)	12 (2.1)	0 (0)	.25

BMI, body mass index.
Data are shown as the number (percentage), mean ± SD, or median (interquartile range) unless otherwise indicated.
*Unpaired *t* tests and χ^2 tests are used for comparing means and percentages by multimorbidity status. Statistical significance ($P < .05$).

The model's performance was evaluated using both the training and test data, with evaluation metrics such as AUC, area under the precision-recall curve, balanced accuracy, precision, recall, specificity, positive predictive value (PPV), negative predictive value (NPV), and F1 score. Given the outcome imbalance, AUC was used as the primary evaluation metric.[28] To further enhance the interpretability of the models, SHapley Additive exPlanations (SHAP) values were calculated to estimate the contribution of each feature to the model's predictive capability.

All ML algorithms were implemented using Python 3.11.5 (Python Software Foundation).

Statistical Analysis

To compare the predictive variables between the fall and nonfall groups, we used a *t* test for continuous variables, and a χ^2 test for categorical variables. The significance threshold for all statistical tests was $P <.05$, and all reported *P* values were 2-sided. All statistical analyses were conducted using R software (version 4.4.0, R Foundation for Statistical Computing, Vienna, Austria).

Results

Of the 1307 participants enrolled during the study period, 684 were excluded, leaving 706 participants for analysis (Figure 1). The mean age was 84.7 ± 6.2 years in the fall group and 83.4 ± 6.7 years in the nonfall group ($P = .07$); 425 (60.2%) were female, and more than 80% were admitted from home. The mean length of hospital stay was 21.4 ± 28.4 days. Falls within 3 months postdischarge were reported by 114 participants (16.1%). The fall group had a higher proportion of individuals with incontinence and significantly lower Lawton IADL scale, BI, and CFS scores than those of the nonfall group (Supplementary Table 2).

We selected 19 features using the filter method, comprising 15 variables from admission data and 4 variables from discharge data (Table 1). The models were constructed using the training data with 4 classifiers, and the Extra Trees classifier demonstrated the highest performance, achieving an AUC of 0.71 ± 0.02, with a precision of 0.26 ± 0.04, recall of 0.59 ± 0.08, PPV of 0.26 ± 0.04, NPV of 0.89 ± 0.02, and an F1 score of 0.36 ± 0.05 (Supplementary Table 4). Validation of the model using the filter method on the test data resulted in an AUC of 0.73, with a precision of 0.29, recall of 0.68, PPV of 0.29, NPV of 0.92, and an F1 score of 0.41. In comparison, models using all 38 variables and those using 7 variables that showed significance in conventional univariate analysis both achieved an AUC of 0.67 (AdaBoost Classifier) (Table 2 and Figure 2). According to these results, the model using the filter method, which achieved the highest AUC, was selected as the final model.

To explain the importance of each variable, we visualized feature importance using SHAP values (Figure 3). Important features included the Lawton IADL scale, CFS (≥4 points), presence of urinary incontinence, GDS-15 (≥5 points), and preadmission residence, all assessed at admission.

Discussion

To our knowledge, this study is the first to develop an ML model for predicting early postdischarge falls among older patients admitted to acute care hospitals through a multicenter collaborative effort. The model demonstrated moderate predictive performance, with an AUC of 0.73. Important features identified included variables related to the Lawton IADL scale, CFS, urinary incontinence, GDS-15, and prehospital residence, all assessed at admission. These findings suggest that the patient's preadmission condition plays a more important role in predicting early postdischarge falls than that of new functional impairments acquired during hospitalization. This model may contribute to the development of fall-prevention strategies during the transition of care from hospital to the community.

However, there are challenges in applying the results of this study to clinical practice. Although the Extra Trees classifier demonstrated moderate predictive accuracy, its low precision and F1 scores suggest that the model may be overestimating fall risk; therefore, the model may have been biased toward nonfall cases because of the data imbalance, given the low fall incidence rate of 16.1%. Although oversampling and stochastic recursive gradient descent are effective for addressing such imbalances, they were not used in this study to

Table 2
Summary of Predictive Performance on the Test Data of 3 Models

	AUC	AUPRC	Accuracy	Balanced Accuracy	Precision	Recall	Specificity	PPV	NPV	F1 Score
Filter method model[*] (Extra Trees classifier)	0.73	0.42	0.69	0.68	0.29	0.68	0.69	0.29	0.92	0.41
All variables model[†] (AdaBoost Classifier)	0.67	0.24	0.70	0.61	0.26	0.47	0.74	0.26	0.88	0.33
P value model[‡] (AdaBoost Classifier)	0.67	0.27	0.59	0.59	0.22	0.59	0.60	0.22	0.88	0.32

AUC, area under the receiver operating characteristic curve; AUPRC, area under the precision-recall curve; PPV, positive predictive value; NPV, negative predictive value.
[*]Filter Method Model: model using features selected by the filter method.
[†]All Variables Model: model using all 38 variables.
[‡]*P* value Model: model using variables that showed significance in univariate analysis.

prioritize the fidelity of the clinical data.[29,30] Instead, class weighting was applied to optimize balanced accuracy. However, the low precision remains a challenge, potentially leading to unnecessary preventive measures for patients not at risk of falling. Nevertheless, the model's high NPV of 0.92 suggests effectiveness in identifying patients with a low likelihood of falling. Additional strategies for addressing imbalanced data should be considered to enhance precision, which could lead to more balanced and practical predictions.

Among the 5 important features extracted, 4 have been previously reported to be associated with falls. The Lawton IADL scale serves as an indicator of physical function and frailty among older adults,[31] whereas the CFS is a comprehensive tool for assessing fall risk.[32] Urinary incontinence is associated with declines in physical and cognitive function,[33,34] and depressive symptoms, as assessed using the GDS-15, are also factors that increase fall risk.[35] These findings were consistent with existing fall risk factors identified among community-dwelling older adults, nursing home residents, and hospitalized patients.[36-39]

On the other hand, variables such as visual impairment, multimorbidity, and cognitive function, which have been reported to be associated with falls,[38,40] were not selected as important features in this analysis. This study focused on predicting falls in the early postdischarge period, and it is likely that these conventional risk factors were not selected as important features during this specific period. Similarly, although variables such as age, living alone, and polypharmacy were identified as features in this analysis and have been reported to be associated with falls,[38] their contribution was lower than that of the top 5 features; thus, they were not considered as highly important in this study.

A notable finding in this study was that the prehospitalization living location was identified as an important feature. Although it is challenging to directly relate this to variables not included in the model, an analysis of patient backgrounds revealed that patients whose living environment changed, such as those admitted from home and discharged to a nonhome setting or those admitted from a nonhome setting and discharged to home, had a significantly higher risk of falls. This suggests that prehospitalization living location may indirectly reflect a patient's living environment, social support, and ability to adapt to changes in their surroundings.[41] In previous studies, variables were often selected arbitrarily based on univariate analysis or prior research findings, which may have resulted in insufficient consideration of variables such as preadmission residence. By using ML, it is possible to analyze all collected data and capture the complex interrelationships between variables. In fact, this study was able to identify preadmission residence as a new risk factor for falls. Future research will need to evaluate residential environment and social factors in more detail and conduct further analysis.

We initially hypothesized that events occurring during hospitalization, such as functional decline indicated by changes in the CFS or Mini-Mental State Examination and falls during hospitalization, would significantly impact early postdischarge falls. However, these factors were not among the 5 most important features. Therefore, to

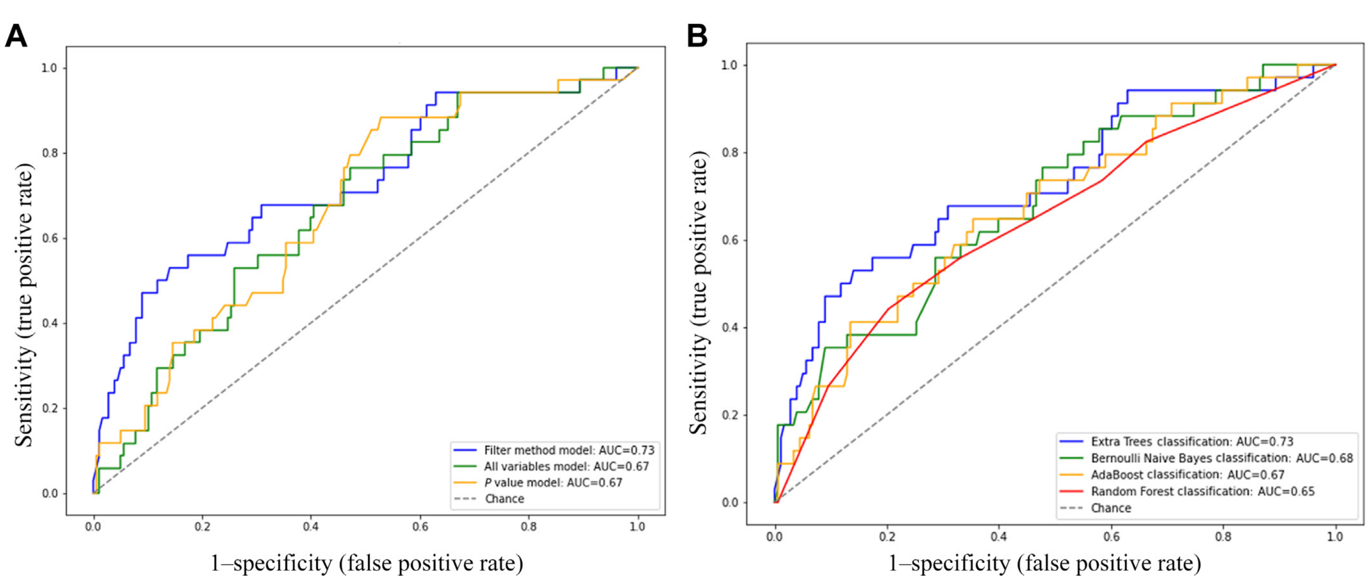

Fig. 2. ROC curves of model performance on the test data using different classifiers and variable sets. The ROC curves compare the performance of models constructed using 3 different variable sets (all variables, significant variables from univariate analysis, and filter method-selected variables) (A), with models constructed using 4 classifiers with features selected by the filter method (B). ROC, receiver operating characteristic; AUC, area under the curve.

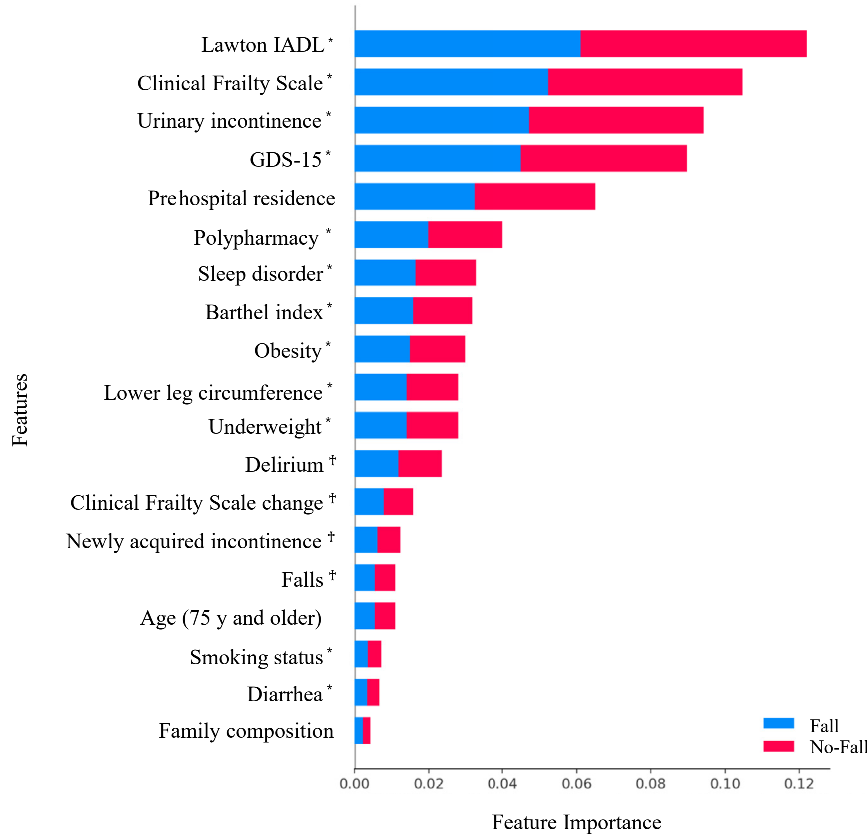

Fig. 3. SHAP value of the Extra Trees classifier. Feature importance ranking of the features included in the Extra Trees classifier. *Assessment items at admission. †Assessment items at discharge. SHAP, SHapley Additive exPlanations; Lawton IADL, Lawton instrumental activities of daily living scale.

prevent HAD and falls, maintaining functional ability though daily living in the community is crucial, regardless of whether an individual is hospitalized.

Our results provide new perspectives on fall-prediction and prevention strategies for older patients in acute care hospitals, with 4 key clinical implications. First, our model was designed as an efficient tool that does not require specialized tests and relies only on basic information available from routine clinical practice, allowing for quick implementation in busy clinical settings. Furthermore, the assessment items used in this model, such as the BI and Lawton IADL scale, are internationally recognized and thus have high applicability across different countries and health care environments. Second, this study considered the impact of functional decline before and after hospitalization and demonstrated that preadmission health status is more critical to early postdischarge falls than HAD, which suggests that fall prevention should include not only care during hospitalization but also routine health management. Third, the introduction of ML eliminated the limitations of variable selection inherent in traditional statistical methods, enabling the simultaneous evaluation of complex interactions among multiple variables and facilitating the discovery of new risk factors. Fourth, we included almost all older adults without exclusion criteria except for age. Although many clinical studies exclude participants with dementia or those living alone because of follow-up difficulties, our approach aimed to capture the complete spectrum of older adults, including previously understudied populations.

These insights suggest that fall prevention should extend beyond the short-term goal of preventing in-hospital falls to encompass continuous risk management from preadmission through postdischarge. Therefore, a shift toward a more comprehensive and sustained fall-prevention approach is anticipated, from care in acute care hospitals to ongoing health management in the community after discharge. Future intervention studies are needed to examine whether rehabilitative and other supportive interventions effectively reduce fall risk in patients identified as high risk during admission assessments.

This study had several limitations. First, the method of fall data collection may have introduced bias. Although fall diaries are considered the gold standard for assessment, we used structured telephone interviews that included detailed inquiries into daily living activities to accommodate participants with cognitive impairment. To improve data reliability, we gathered specific information on daily activities and fall circumstances and, for cases of cognitive impairment, supplemented this information by interviewing family caregivers. However, the methodologic limitations inherent in telephone interviews may have influenced fall reporting accuracy. Second, a significant number of patients ($n = 370$) were excluded owing to missing data. The high attrition rate was likely due in part to our inclusive study design, which included almost all older adults and did not exclude participants with dementia or those living alone, who were difficult to follow up. Future studies will need to establish more reliable follow-up methods, such as combining multiple data collection methods and conducting home visits. Third, the sample size was limited and the number of positive cases was small, resulting in some restrictions on the model's performance. Furthermore, the features used did not capture all fall risk factors, such as previous fall history and detailed medication information. Future research should aim to improve model performance by optimizing feature selection and increasing sample size. Finally, although this was a multicenter collaborative study, it was conducted in geriatric wards of acute care hospitals, which may limit the generalizability of the results. Future studies are needed to determine if similar outcome can be obtained in other health care settings.

Conclusions and Implications

We developed an ML model to predict early postdischarge falls among older patients hospitalized in acute care hospitals. The Extra Trees classifier achieved a predictive performance with an AUC of 0.73. Important features identified included variables related to the Lawton IADL scale, CFS, urinary incontinence, GDS-15, and preadmission residence, all assessed at admission. These results indicate the potential to develop a model that can easily predict early postdischarge falls among older hospitalized patients using ML.

Disclosure

The authors declare no conflicts of interest.

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Supplementary Data

Supplementary data related to this article can be found online at https://doi.org/10.1016/j.jamda.2024.105414.

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