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Original Article

AI-driven fall risk prediction in inpatients: Development, validation, and comparative evaluation

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ABSTRACT

Background & Aim: Falls among hospitalized patients pose severe consequences, necessitating accurate risk prediction. Traditional assessment tools rely on cross-sectional data and lack dynamic analysis, limiting clinical applicability. This study developed an AI-based fall risk prediction model using supervised learning techniques to enhance predictive accuracy and clinical integration.

Methods & Materials: This study was conducted at a medical center in Taiwan, excluding pediatric patients due to non-disease-related fall factors. Fall cases were obtained from hospital records, and non-fall cases were stratified based on age and gender to create a balanced 1:1 dataset.

A total of 52 predictive variables were identified and refined to 39 through expert review. The AI model was compared with MORSE, STRATIFY, and HII-FRM using supervised learning with 10-fold cross-validation. Performance was evaluated based on accuracy, sensitivity, and specificity.

Results: The results demonstrated that the AI-based model significantly outperformed traditional fall risk assessment tools in accuracy, sensitivity, and specificity. More importantly, the model's superior predictive power allows for real-time risk assessment and seamless integration into clinical decision support systems. This integration can enable timely interventions, optimize patient safety protocols, and ultimately reduce fall-related incidents in hospitalized settings.

Conclusion: By automating risk assessment, the AI model can alleviate the workload of healthcare professionals, reducing the time required for manual evaluations and minimizing subjective biases in clinical decision-making. This not only enhances operational efficiency but also allows nursing staff to allocate more time to direct patient care. These findings underscore the transformative potential of AI-driven approaches in healthcare, improving patient safety through data-driven.

Introduction

Falls are a fundamental concept of patient safety in healthcare, representing a critical issue that needs to be addressed to prevent patients from experiencing harm due to accidents or errors during hospitalization (1). For the purposes of this study, a "fall" is operationally defined as an unintentional event where an individual comes to rest on the ground or a lower level, not due to major intrinsic factors such as strokes or seizures, or external overwhelming hazards. Falls are a significant public health issue globally. Over 680,000 fatal falls occur each year, with 80% in low- and middle-income countries, like many countries in the Asia-Pacific region (2). A review of 104 studies revealed a global prevalence estimate of 26.5% for falls in older people and the prevalence variously ranged

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from 12.5% to 73% in Asia (3). In 2015, fall-related medical expenses in the U.S. surpassed 50 billion dollars, and by 2020, they were expected to increase to 55 billion dollars (4). Approximately 37.3 million non-fatal falls require medical attention, and those who fall and suffer a disability are at significant risk of long-term care and institutionalization; therefore, the financial costs of fall-related injuries are substantial and compelling prevention strategies could create a net savings of over US$ 120 million each year (2).

In various environments where falls occur, falls during hospitalization lead to the most serious consequences. According to the guidelines from the National Institute for Health and Care Excellence (NICE) (5), hospitalized patients face falling risks due to poor health, comorbidities, anesthetics, pain, medications, polypharmacy, and muscle weakness. However, many patients are unaware of the risk of falling (6-9). Approximately 25% of falls in hospitals result in injuries, including fractures, soft tissue damage, and fear of falling (6-7). Therefore, preventing falls among hospitalized patients is the most critical aspect of fall prevention that warrants the highest attention. Given the significant burden of falls on individuals and healthcare systems, it is crucial to prioritize fall prevention strategies by identifying individuals at high risk for falling. Mitigating risk factors can help decrease the likelihood of falls.

The identification and analysis of risk factors can provide valuable insights into the multifaceted factors that contribute to falls in individuals, which can facilitate the development of more precise and efficient fall detection models. Generally, fall risk factors are categorized into two groups: intrinsic and environmental factors. Intrinsic factors include not only demographic variables (4) but also various medical conditions and physical impairments that have been linked to an increased risk of falling. These include muscle weakness, gait and balance issues, poor vision, postural hypotension, and chronic diseases such as osteoporosis, stroke, cognitive impairment, epilepsy, and dementia. Additionally, medications used for mental disorders, diabetes, cardiovascular conditions, and nonsteroidal anti-inflammatory drugs (NSAIDs) are strongly associated with a higher fall risk. On the other hand, extrinsic factors, such as unsafe living conditions and hazardous environments, are significant contributors to falls (4, 6). In a review of the literature on the causes of falls, various factors related to biology, behavior, and environment can increase the risk of falls, as indicated by a comprehensive review of published literature in the supplement file 1 (1, 10-12). Biological risk factors refer to factors within an individual's body, including demographics (age, gender), medical history (chronic diseases such as arthritis, Parkinson's disease, dementia or stroke, history of falls), health condition (sensory deficits, cognitive impairment, urinary incontinence), motor function (activities of daily living, muscle strength, flexibility, balance, and gait) and medication side effects (sedative/psychotropic medications) (1, 12). Behavioral risk factors are fear of falling, lack of physical activity or exercise, cognitive impairment, risk-taking behaviors, alcohol or drug use, inadequate diet, inappropriate footwear, and spectacles (11, 13). Environmental risk factors contain environmental hazards, social networks, and unmanaged risk factors, such as staffing (10).

In clinical practice, it is common to use a cross-sectional indicator, such as the “Fall Risk Assessment Scale” to evaluate whether individual hospitalized patients are at risk of falling. Systematic reviews uncovered 38 fall risk scales with 11 to 15 scales for in-hospital patients (14, 15), and the most frequently used scales in hospitals were the St. Thomas Risk Assessment Tool in Falling Elderly Inpatients (STATIFY), MORSE Fall Scale, STATIFY, and HENDRICH Fall Risk Model (HII-FRM) (15, 6). The STATIFY scale evaluates the likelihood of falls among elderly patients during hospitalization, and this 5-item scale has a total score of 5 points, with a score of greater than 2 indicating a high-risk group for falls (17). The MORSE Fall Scale is to assess and detect high-risk groups for falls among hospitalized patients, and it consists of 6 items, with a total score of 125 points and scores of

45 or above indicating a high-risk group for falls (18). The HII-FRM is also to assess whether hospitalized patients are at high risk of falls, consisting of 8 items with a score range of 0 to 14, and a total score greater than five is defined as a high-risk group for falls (19). The items that are common among these three fall risk assessments are mental status and mobility/transferring. In contrast, the remaining items differ between the assessments and include gender, history of falls, elimination (frequent toileting), visual impairment, comorbidities, ambulatory aid, IV/Heparin Lock, and medication. Some key factors were excluded from fall risk assessment, such as health conditions, risk-taking behaviors, environmental hazards, and hospital context. Nevertheless, the complexity and interrelatedness of fall risk factors, combined with the lack of consensus in fall risk assessments and the heavy workload of nurses, have created a significant challenge in clinical practice for identifying possible risk factors in advance and accurately predicting falls. Fall risk assessment tools face challenges such as the need for greater consensus, incomplete assessments, and reliance on human judgment. Accordingly, a fall risk assessment method suitable for clinical use during hospitalization must be able to provide personalized evaluation, incorporate more factors influencing falls, dynamically update variables over time, and reduce the subjectivity of caregivers' judgments in the assessment process.

In recent years, artificial intelligence (AI) technology has rapidly emerged, becoming a popular tool across various fields. The use of AI in the healthcare sector to enhance patient safety is also increasingly prevalent, bringing revolutionary changes to clinical care. With its efficient automation, precise data analysis, and powerful predictive capabilities, AI is transforming the operational models of traditional industries. The core technology of artificial intelligence (AI) is machine learning, which can be categorized into two main types: supervised learning and unsupervised learning. Among these, supervised learning is more widely applied in practice due to its clear learning objectives and strong predictive capabilities. It is particularly important in the healthcare field, where learning from past care experience data helps to achieve relatively stable and accurate target labels (i.e., expected outcomes). This not only reduces human errors but also enhances and ensures the quality of care, fostering a better doctor-patient relationship. In recent years, a growing number of studies have applied machine learning techniques in artificial intelligence to predict disease progression, demonstrating highly promising results. AI-driven methods have the potential to offer more accurate and comprehensive fall risk assessments, which can support healthcare professionals in devising more tailored and effective fall prevention strategies for their patients (20).

As previously mentioned, many clinical studies have traditionally relied on cross-sectional fall risk assessment tools, such as MORSE, STRATIFY, and HIIFRM, to identify hospitalized patients at risk of falls. However, with the rapid advancements in artificial intelligence (AI), there is a growing acknowledgment that AI-based methods offer a more dynamic approach, capable of integrating a wider array of influencing factors, such as medications, comorbidities, and time-sensitive variables. Despite this recognition, there is currently a lack of systematic comparisons between the accuracy of these two approaches under the same conditions.

This study addresses this significant gap in the literature. To that end, we have gathered data from fall detection systems using electronic administrative data, electronic medical records (EMR), and nursing information systems (NIS), including patient demographics, medical history, medication records, and nursing assessments. These datasets were used to compare the predictive performance of traditional fall risk assessment tools and AI-based methods in identifying fall risks among hospitalized patients. The main goal of this research is to provide a more evidence-based foundation for selecting the most effective fall risk assessment approach, thereby improving decision-making in clinical risk management and reducing the risk of falls in hospitalized settings.

Methods

Design

This study employs a case-control design to systematically compare the predictive accuracy of fall risk between three traditional high-risk fall assessment scales and a fall risk prediction model developed using supervised learning techniques in machine learning. The same sample was used as the basis for evaluation to ensure consistency and comparability.

Source of data

The study obtained approval from the medical ethical review committee at the participating hospital (approval No. 10102/120806). Data were collected from multiple sources, including demographic and clinical information from the hospital's electronic medical records (EMR) and hospital information system (HIS). These data sources included details such as gender, date of birth, patient medical history, diagnosis, detailed medical prescriptions, and administrative information. Additionally, care data were extracted from the nursing information system (NIS), which included nursing assessments and nursing directive codes. This comprehensive approach ensured the collection of relevant data for both fall and non-fall cases.

Study population

The study population consisted of inpatients from a large regional teaching hospital in Southern Taiwan over a 10-year period. Fall incidents were identified from the Taiwan Patient-Safety Reporting (TPR) system. Due to the adoption of the ICD-10 system in Taiwan in 2016, which introduced a one-to-many mismatch issue with ICD-9 codes, this study focused on data from the 10 years preceding 2015 to maintain coding consistency.

Fall group: The fall group consists of all reported fall cases collected from the patient safety reporting system in the case hospital. The dataset includes 197 adult inpatients from departments such as internal medicine, surgery, general medicine, and obstetrics and gynecology. Pediatric departments were excluded because many pediatric falls are attributed to non-disease-related factors (21), Unlike adult inpatients, whose fall risks are associated with chronic illnesses and physiological decline, pediatric falls are largely behavior-driven. As this study focuses on disease-related fall risks**,** pediatric cases were not included.

Non-fall group: Non-fall participants were sampled from the same departments as the fall group, based on the age and gender distribution of the fall cases, to create a balanced 1:1 dataset for comparison.

The following exclusion criteria were applied: (1) Incomplete medical records**,** where essential variables required for predictive modeling were missing; (2) Trauma-related falls**,** where falls resulted from external injuries rather than intrinsic health conditions; (3) ICU patients**,** whose fall risk is influenced by continuous monitoring and specialized care; (4) Patients with severe neurodegenerative diseases**,** such as advanced dementia or Parkinson’s disease, to avoid introducing bias unrelated to general inpatient fall risk factors. These exclusions ensured that the dataset was clinically relevant for evaluating fall risk among general adult inpatients and provided a robust dataset for predictive modeling Due to the retrospective study design and the use of secondary data, post-hoc evaluation indicated that the sample size was sufficient for statistical modeling, with model performance metrics supporting its adequacy.

Sampling and model construction

To construct a classification model, each inpatient in the medical dataset was labeled based on whether they had a recorded fall incident in the patient safety reporting system. Given the relatively low proportion of fall cases, it was necessary to address the class imbalance to ensure accurate predictions. To achieve this, we collaborated with the information department to randomly sample non-fall inpatients from the same hospital departments represented by the fall cases.

Initially, non-fall patients were sampled at a five-fold ratio relative to the fall cases to create a diverse non-fall dataset. From this dataset, 197 non-fall cases were randomly selected and combined with 197 fall cases, resulting in a balanced total sample size of 394 patients. To enhance the model's robustness, this random sampling process was repeated 30 times, generating 30 distinct training datasets, each maintaining a 1:1 ratio of fall to non-fall cases. The final model predictions were averaged across these samples to ensure consistent and reliable performance. Similar sample sizes have been used in previous fall risk prediction studies (20, 22).

The predictive model was developed using supervised learning techniques and validated through 10-fold cross-validation. The cross-validation results were aggregated across all training datasets to confirm the model's robustness and generalizability.

Predictor and outcome variables

The study aimed to expand the collection of predictors contributing to fall risk and systematically evaluate their impact. The predictive variables were selected and refined through a Delphi method, involving a panel of six clinical experts from diverse disciplines, including nursing, medicine, epidemiology, and healthcare quality. The process consisted of three iterative rounds. The selection and refinement of predictive variables followed a systematic and rigorous process:

1. System literature review phase: In phase one, we conducted a systematic review of all fall-related factors from databases such as PubMed, ScienceDirect, IEEE Xplore, Web of Science, and Google Scholar. A total of 52 potential predictors were identified and categorized into five groups: demographic factors, physiological factors, psychological factors, pharmaceutical factors, and other factors. Experts independently scored 53 variables on a four-point Likert scale based on relevance, and variables with a CVI score < 0.70 were excluded.
2. Expert consultation review: The research team submitted a data request to the hospital's information department, providing a list of fall patient records that matched the research variables from phase one (see supplementary file 1) and a list of medication order codes (see Supplementary file 2). Six clinical nursing professionals then reviewed these fall-related factors using the Delphi method in phase II. After resolving inconsistencies among experts, 39 predictors with a Content Validity Index (CVI) of 0.83 were selected for analysis.
3. Integration with traditional scales: In the third phase, 27 predictors with full consensus were identified, achieving a CVI score of ≥0.83. Following a review of fall risk assessment tools, 13 overlapping variables were retained by domain experts. After removing redundancies, a final list of 39 predictors was established.

The final set of predictive variables included 27 variables derived from the Delphi process and CVI validation, along with 13 variables from traditional fall assessment tools. Additionally, 2 new variables were identified during the model refinement process, bringing the total to 39 predictive variables. These additional variables were deemed clinically relevant and were included to enhance the comprehensiveness of the model.

To evaluate and compare fall risk prediction accuracy, we incorporated three widely used fall risk assessment tools—MORSE, STRATIFY, and HII-FRM —as key predictors. The MORSE, STRATIFY, and HII-FRM tools were selected for comparison because they are widely used and validated in clinical settings. Each represents a distinct approach to fall risk assessment, providing a comprehensive benchmark for evaluating the AI model. MORSE is known for its simplicity and applicability across various patient populations, STRATIFY is validated for acute inpatient settings, and HII-FRM is popular for older adult populations due to its inclusion of cognitive and physical factors.

Below is a brief overview of these tools and their unique features: The MORSE is a widely used tool for assessing fall risk in hospitalized patients. It evaluates six key factors: history of falls, secondary diagnosis, ambulatory aid, intravenous therapy, gait, and mental status. Each factor is assigned a score, and the total score categorizes patients into low, moderate, or high fall risk. The MFS is known for its simplicity and quick administration, making it practical for routine use in clinical settings. The STRATIFY is specifically designed for elderly inpatients. It assesses five factors: history of falls, agitation, visual impairment, frequent toileting, and transfer and mobility status. The tool provides a binary scoring system (yes/no) for each item, offering a straightforward way to identify patients at risk. STRATIFY is particularly valued for its focus on geriatric populations and its emphasis on mobility and environmental factors. The HII-FRM incorporates a broader range of risk factors, including confusion/disorientation, symptomatic depression, altered elimination, dizziness/vertigo, gender, anti-epileptic and benzodiazepine medications, and poor performance in the "Get-Up-and-Go" test. This tool is notable for integrating both physical and medication-related factors, providing a comprehensive assessment of fall risk. The inclusion of medication use as a variable highlights its utility in environments with complex pharmacological considerations.

The traditional tools were selected based on their prevalence in clinical practice and their established methodologies. Each tool assesses fall risk using predefined variables. However, they share several limitations, including reliance on static variable selection, inability to handle complex interactions, and low sensitivity in diverse patient populations. The AI model developed in this study addresses these limitations by incorporating a comprehensive set of predictors and leveraging machine learning algorithms to dynamically assess fall risk and to prove if it has significant improvements in accuracy, sensitivity, and specificity compared to traditional tools.

The predictors of these tools were categorized into two types: one-time assessment variables and multiple-time assessment variables. The one-time variables were collected upon admission and included demographic information, admission diagnosis, self-care ability, consciousness, emotional state, visual impairment, malnutrition, sleep disorders, and the presence of a prosthetic limb. The multiple-time variables were measured at key intervals throughout hospitalization and included lower limb muscle strength, surgical records, catheter usage, medication records, and fall risk scores. Data collection was conducted at specific time points: within the first 24 hours of admission, during the initial period after the first 24 hours, at the highest value recorded during hospitalization, and at the last recorded value prior to a fall event (for the fall group) or discharge (for the non-fall group).

Statistical analysis

Once the data was collected, the researchers performed data cleaning and data transformation as part of the data preprocessing stage. This was done to ensure the data was accurate and ready for analysis.

This study employed a stepwise approach to optimize classification performance. we utilized the open-source data mining software WEKA 3.8.3 for conducting our experiments, and we utilized WEKA to develop predictive models using Decision Trees (DT), Random Forest (RF), and Logistic Regression (LGR), which were evaluated to determine the most effective baseline model. Based on performance metrics such as accuracy, sensitivity, and specificity, and its results were further compared with three traditional fall risk assessment scales (MORSE, STRATIFY, and HII-FRM) to evaluate its clinical utility

Decision Trees, on the other hand, employ a hierarchical tree structure for decision-making, making them suitable for both classification and regression tasks. They can provide categorical or numerical predictions, which allows them to be expanded into classification trees, regression trees, or combined classification and regression trees.

Random Forest is an ensemble technique that consists of multiple decision trees. Similar to DTs, RF can handle both classification and regression tasks. For classification, each tree in the Random Forest votes on a category, and the final decision is based on majority voting, while for regression tasks, the final output is the average of all tree predictions.

while linear regression typically deals with continuous dependent variables, Logistic Regression focuses on categorical variables, particularly in the context of binary classification. Beyond binary classification, LGR can be extended to accommodate multi-class scenarios using approaches like multinomial or ordinal logistic regression. The DT, LGR, and RF single classifier models were constructed using WEKA's C4.5, SimpleLogistic, and RandomForest modules, respectively.

Furthermore, we enhanced the fall risk prediction models by implementing an ensemble classifier model in the second step. Specifically, we applied Adaboost (Adaptive Boosting) and Bagging (Bootstrap Aggregating) to improve the model's predictive accuracy and robustness. AdaBoost algorithm is one of the most popular ensemble methods, designed to improve the accuracy of base classifiers. In this study, AdaBoost was implemented using the AdaBoostM1 module in WEKA to further strengthen the predictive performance of the classification models. The AdaBoost model was constructed using the AdaBoostM1 module in WEKA 3.8.3, with decision trees as the base classifiers. Misclassified samples were iteratively assigned higher weights, enabling the ensemble to improve prediction accuracy by focusing on difficult cases. The model underwent nested cross-validation, with hyperparameters (e.g., boosting rounds, tree depth) optimized through 10-fold cross-validation on the training set. Previous research has shown that classifiers paired with AdaBoost often achieve significantly better classification performance compared to standalone models.

We also applied the Bagging algorithm which is a popular ensemble method that improves stability and accuracy by combining multiple models trained on different subsets of data. Bagging, or Bootstrap Aggregating, is an ensemble learning method designed to improve the stability and accuracy of machine learning models by reducing variance. Multiple subsets of the dataset were created through random sampling with replacement (bootstrapping), and a separate decision tree was trained on each subset. The final prediction was obtained by aggregating the outputs of all trees, typically through majority voting. Bagging is particularly effective in reducing overfitting, a common issue with decision trees, and enhances the model's robustness by minimizing sensitivity to noise and small changes in the dataset. Previous research indicates that Bagging is particularly effective in reducing variance for high-variance models like decision trees. In this study, Bagging was implemented using the Bagging module in WEKA, allowing us to boost the predictive performance of our models.

Last, the results of the AI best model were further compared with three traditional fall risk assessment scales (MORSE, STRATIFY, and HII-FRM) to evaluate its predictive performance and clinical utility.

To address the issue of class imbalance commonly observed in health-related datasets, which can bias machine learning algorithms towards the majority class, we employed cost-sensitive learning and data resampling techniques. Various resampling methods, including under-sampling, oversampling, synthetic minority oversampling technique (SMOTE), and class weighting, were explored to assess their impact on classifier performance. These techniques aimed to mitigate the bias caused by imbalanced class distribution and improve the accuracy of our fall prediction models.

Given that hyperparameter tuning can greatly influence the performance of classifiers, we leveraged WEKA's CV Parameter Selection meta-learner module to optimize the hyperparameters for each model. The specifics of parameter tuning for each classifier are detailed in Table 1. Hyperparameter optimization was conducted by systematically testing a range of values for key parameters in each classifier. For the decision tree (DT), the confidence factor was tested within the range of 0.1 to 0.5, with increments of 0.05, and the minimum number of instances per leaf was tested from 2 to 20, with increments of 1. For logistic regression (LGR), the ridge value was fixed at 1.0E-8 based on prior research. For random forest (RF), the number of trees was varied from 50 to 250 in increments of 10.

The tuning process involved a grid search to test all possible parameter combinations, with nested cross-validation applied to evaluate the performance of each configuration. Performance metrics, including accuracy, sensitivity, and specificity, were recorded for each combination. The final optimal settings were determined based on the configuration that achieved the highest predictive performance.

Table 1. Hyperparameter Tuning in WEKA

Technique	Hyperparameters	Range	Increment
DT	Confident factor	0.1-0.5	0.05
	Minimum number of instances per leaf	2-20	1
LGR	Ridge value = 1.0E-8	-	NA
RF	Number of trees	50-250	10

Development vs. validation

A two-layer nested cross-validation approach was employed to develop and evaluate classifiers. The dataset was split into training and holdout test sets in a 2:1 ratio, repeated ten times to create 30 training and test set pairs. Within the inner layer, 10-fold cross-validation was performed on the training set to determine optimal hyperparameters. The classifiers were then built using the entire training set with the optimal hyperparameters and tested on the holdout test set.

Once the best classifier is identified from the training set tests, it is applied with the optimal parameter settings to assess performance using the validation set. The confusion matrix was used to evaluate the performance of each prediction model (Table 2). In this context, true positive (TP) refers to the number of inpatients who were correctly identified by the model as being at risk of falling; true negative (TN) refers to the number of non-fall injury inpatients correctly classified as not being at risk of falling; false positive (FP) indicates the number of non-fall injury in-patients who were incorrectly predicted to be at risk of falling; and false negative (FN) represents the number of inpatients at risk of falling who were incorrectly classified as not being at risk of falling.

Table 2. Confusion matrix

		Predicted class	
		Falling injury	Non-falling injury
Actual class	Falling injury	*TP*	*FN*
	Non-falling injury	*FP*	*TN*

Based on the confusion matrix data, three classification performance metrics, namely accuracy, sensitivity, and specificity, can be obtained using the following equations:

$$Accuracy=(TP+TN)/(TP+FP+FN+TN)$$
$$Sensitivity = TP / (TP+FN)$$
$$Specificity = TN / (TN+FP)$$

The area under the receiver operating characteristic curve (AUC) was used as a measure of model performance, where higher AUC values reflect greater accuracy. According to Hosmer and Lemeshow (23), a model is considered to have excellent predictive performance, if AUC is $\geq$ 0.9, good performance if 0.9 > AUC $\geq$ 0.8, and fair performance if 0.8 > AUC $\geq$ 0.7.

Model comparisons were conducted using the Friedman and Nemenyi tests. Logistic regression was used to analyze the associations between clinical features and the outcome, evaluating model discrimination and fit using accuracy and Hosmer-Lemeshow statistics.

Statistical analyses were performed using SPSS 21, considering two-tailed p-values <0.05 as significant. Finally, the developed fall prediction model meeting the specified criteria was compared to the performance of existing scales.

Results

Participants

A total of 197 hospitalized patients who experienced falls were collected from the hospital's patient safety reporting system as the fall-participant group for this study. The percentage of patients from each department in the fall-participant dataset was used to determine the number of non-fall patients to select from each department. We randomized 985 non-fall participants from a total of 38,447 medical records, including 560 for the internal department, 125 for the medical department, 290 for the surgical department, and 10 for the obstetrics and gynecology department. The descriptive statistics of both groups are presented in Table 3. The results indicate that, although the dataset for non-fall patients is much larger than that for fall patients, there is no significant difference in the distribution of basic data between the two groups.

Table 3. Characteristics of the sample population

Variables	Range	Fall dataset (n=197)	Non-Fall dataset(n=985)	P value
Gender	Male Female	135 (68.5%) 62 (31.5%)	519 (52.7%) 466 (47.3%)	.000
Age	Max/min Mean (SD)	19/95 64.9(17.2)	19/96 64.4(17.9)	.328
Fall history	Y N	12(6.1%) 185(93.9%)	81(8.2%) 904(91.8%)	.166

Performance comparison of DT and LGR in fall prediction model

Table 4 lists the performance results of the machine learning models. The accuracy of DT (C4.5) ranged from 68.1% to 71.8%, while LGR achieved 71.1% to 75.2%. Although the highest sensitivity obtained using LGR was acceptable, its average sensitivity was still lower than that of DT. RF, despite being an advanced version based on decision trees, showed slightly lower classification accuracy than DT, although its other metrics were superior to those of the equation-based LGR. In terms of accuracy, all values obtained with LGR were lower than those of DT. Additionally, the average sensitivity and specificity for DT were 0.736 and 0.699, respectively. The sensitivity and specificity for RF were 0.734 and 0.719, respectively. In contrast, the average sensitivity and specificity for LGR were 0.721 and 0.699. On the other hand, while DT's sensitivity was higher than that of LGR, their specificity results were the same. However, the primary concern in this study is cases with label Y (fall incidents). Therefore, overall, the fall risk prediction model constructed using the C4.5 algorithm, which is based on decision trees, performed best.

Table 4. Evaluation results between the different classifiers

Classifier		Accuracy	Sensitivity	Specificity	AUC
DT	Max	74.6%	75.1%	74.1%	77%
	Min	68.1%	67.5%	68.5%	
	Average	71.8%	73.6%	69.9%	
LGR	Max	74.1%	75.1%	73.1%	71%
	Min	67.7%	68.5%	67.0%	
	Average	71.1%	72.1%	69.9%	
RF	Max	73.2%	74.7%	73.2%	74%
	Min	70.1%	72.1%	70.5%	
	Average	71.7%	73.4%	71.9%	

Performance comparison of ensemble classifiers in fall prediction model

We compared the performance of ensemble classifiers that combined AdaBoost and bagging with DT (AdaBoost+ DT and Bagging with DT) in fall prediction. Using default parameter values in Weka, training was conducted on 30 samples, and averages were calculated. Table 5 showed improved specificities for both combinations, with AdaBoost+ DT achieving a higher specificity compared to Bagging+DT. Sensitivity slightly increased for AdaBoost+ DT but decreased for Bagging+DT. In terms of accuracy, AdaBoost+ DT outperformed Bagging+DT, achieving an accuracy of 72.6% compared to 70.9%. These findings suggest that AdaBoost+ DT demonstrated the most favorable results.

The fall prediction model developed using AdaBoost+DT included the attributes in the fall assessment scales and incorporated additional risk factors, such as age, number of hospitalizations, medications, medical history, lower limb prostheses, malnutrition, lower limb muscle strength, Barthel Index, daily activity, time associated with increased risk falls, patient's companions, high-risk group in risk fall assessment, anemia, orthostatic hypotension, sleep disorders, and surgery during hospitalization (please refer to supplement file 1).

Table 5. Evaluation results between the different ensemble classifiers

Classifier		Accuracy	Sensitivity	Specificity
AdaBoost+DT	Max	77.2%	79.7%	74.6%
	Min	66.8%	69.5%	64.0%
	Average	72.6%	74.5%	70.8%
Bagging+DT	Max	73.6%	73.1%	74.1%
	Min	67.5%	68.0%	67.0%
	Average	70.9%	71.8%	70.0%

Model performance

The performance of a fall prediction model created using machine learning techniques, specifically AdaBoost+ DT, was compared to that of conventional fall assessment scales (MORSE, STRATIFY, and HII-FRM) to assess its predictive capabilities. The experimental results, as summarized in Table 6, indicated that the average accuracy of the three conventional scales was below 60.0%, with STRATIFY achieving the lowest accuracy at 43%. In contrast, the patient falls prediction model developed in this study conducted a significantly higher accuracy of 72.6%. By utilizing supervised learning technology, the predictive efficiency of the model surpassed that of commonly used clinical prediction tools.

Table 6. Comparison of prediction performance of different fall scales

Fall risk assessments		Accuracy	Sensitivity	Specificity
MORSE	Max	54.3%	15.7%	96.5%
	Min	50.8%	5.1%	88.8%
	Average	52.8%	13.7%	92.1%
STRATIFY	Max	48.7%	20.6%	93.9%
	Min	39.8%	3.6%	60.4%
	Average	42.6%	18.8%	66.5%
HII-FRM	Max	56.6%	61.9%	94.9%
	Min	46.7%	6.6%	44.2%
	Average	52.5%	46.1%	59.1%
AdaBoost by DT	Max	77.2%	79.7%	74.6%
	Min	66.8%	69.5%	64.0%
	Average	72.6%	74.5%	70.8%

Furthermore, analyzing the sensitivity and specificity results revealed significant variation among the three prediction tools when applied to the 30 datasets. Compared to the specificity values, the sensitivity values were notably low, indicating that the scales' identification of high-risk patients was not stringent enough. This limitation contributed to the low index values and highlighted the scales' inadequacy in incorporating influential factors.

The comparison with standard clinical assessment scales demonstrated that the fall prediction model developed in this study effectively addressed the deficiencies of the existing scales. It provided a more accurate and comprehensive assessment of fall risk in patients, filling the gaps present in current clinical practice.

Discussion

When conducting a fall risk assessment, several common factors are typically considered, such as history of falls, gait/mobility, mental status, vision impairment, toileting, sex, ambulatory aid, medications, chronic health conditions, consciousness, and intravenous therapy. However, our findings revealed additional factors that were not commonly included in existing fall assessment scales. These factors included age, lower limb prosthesis, muscle power, Barthel Index, medications (such as drug-related orthostatic hypotension, diuretics, anticoagulants, antihistamines, analgesics/anesthetics, sedatives/psychotropic drugs, and drug-induced risk of falls), malnutrition, anemia or orthostatic hypotension, sleep disorders, medical history, surgery, patient companion, and activities during falls. By incorporating these additional factors into our evaluation, we aimed to provide a more comprehensive and accurate fall risk assessment.

Age is a well-established factor associated with an increased risk of falls (24-27). Aging is related to various physiological and functional changes which are the common risk fall factors. For example, age-related loss of muscle mass and strength can lead to impaired balance and instability, making individuals an increased risk of falls (28). Age-related vision changes including decreased visual acuity, impaired depth perception, and reduced peripheral vision can affect the ability to detect hazards in the environment and increase the risk of falls (25). Age-related cognitive decline or developing chronic health conditions, impairing an individual's ability to navigate their surroundings safely and increasing the risk of falls. Chronic health conditions as identified in our findings, including cardiovascular disease, neurological disorders, stroke, musculoskeletal disorders, dementia, and depression, it is also supported by previous studies (24, 26). Older adults often take multiple medications for various health conditions that can have side effects such as dizziness, drowsiness, or changes in blood pressure, which can contribute to falls (29).

The factors of lower limb prosthesis, muscle power, and Barthel Index provide valuable insights into an individual's functional status and physical capabilities. The use of a prosthesis presents challenges related to fit and alignment, socket discomfort or instability, reduced sensation, and proprioception which can result in decreased control over the prosthesis and further hinder the ability to detect and correct postural instabilities (30). In addition, muscle weakness can lead to difficulties in balance and gait, characterized by altered patterns due to limb loss that can impose functional limitations on individuals, impacting their ability to perform daily activities and increasing the likelihood of falls (31). Muscle power and the Barthel Index are the tools for identifying individuals who may be more vulnerable to falls due to mobility limitations, muscle weakness, or difficulties in performing daily activities (26).

Various types of medications used during hospitalization can contribute to an increased risk of falls (29). This study revealed the new findings associated with fall risk on the following medications: drug-related orthostatic hypotension, antihistamines, analgesics/anesthetics, sedatives/psychotropic drugs, diuretics, anticoagulants, and drug-induced risk of falls (see supplement file 2). Many medications can cause drowsiness, dizziness, muscle relaxation, and impaired coordination, increasing the risk of falls. For example, alpha-blockers and beta-blockers can cause orthostatic hypotension, leading to lightheadedness or dizziness; benzodiazepines (e.g., lorazepam, diazepam) and non-benzodiazepine sedative-hypnotics (e.g., zolpidem, zaleplon) can cause drowsiness, dizziness, and muscle relaxation; nonsteroidal anti-inflammatory drugs (NSAIDs) (e.g., indomethacin or ketorolac), opioids (e.g., morphine, oxycodone), antihistamines, and anesthetics can cause sedation, drowsiness, confusion, or muscle weakness (29). Anticoagulants, such as warfarin, rivaroxaban, and apixaban, are not directly associated with an increased risk of falls. However, it is worth noting that patients who experience falls are often older and more prone to thrombotic complications due to underlying disease states. The increased risk of falls in these patients is primarily attributed to age-related factors and underlying health conditions rather than the anticoagulant drugs themselves (32). Diuretics (e.g., hydrochlorothiazide or furosemide) increase urine production, leading to fluid and electrolyte imbalances, dehydration, or changes in blood pressure which effects can cause symptoms like dizziness, lightheadedness, or orthostatic hypotension, potentially increasing the risk of falls (33).

Other factors, such as malnutrition, anemia or orthostatic hypotension, sleep disorders, medical history, and surgery are all related to physiological and functional changes. Malnutrition can lead to muscle weakness, reduced bone density, and impaired balance which may also cause fatigue and cognitive impairments (34). Anemia or orthostatic hypotension can cause dizziness, lightheadedness, and a sense of imbalance (35). Sleep disorders can impair attention, reaction time, and coordination, and reduce cognitive function. Medical history or comorbidities are similar to chronic health conditions and can contribute to an increased risk of falls (36). Individuals having surgery may experience postoperative pain, reduced muscle strength, limited range of motion, or changes in gait patterns can contribute to instability and an increased risk of falls during the recovery period (37).

The factors mentioned above are interconnected and impact an individual's overall physical health, physiological stability, cognitive function, and psychological well-being, all of which contribute to fall risk. Traditional tools are limited by their reliance on static scoring systems, a narrow set of variables, and subjectivity in manual assessments. In contrast, the AI model addresses these limitations by using advanced algorithms that incorporate a broader range of factors, analyze dynamic variable interactions, and automate the risk assessment process. This results in higher predictive performance and seamless integration into clinical decision support systems, enabling real-time risk evaluation and timely interventions

In the study, we utilize the AI methods with AdaBoost+ DT model has demonstrated the highest accuracy in predicting falls among inpatients. The AdaBoost+DT model outperformed all other methods, including single classifiers, ensemble classifiers, and traditional fall risk assessment tools, due to its ability to iteratively correct misclassified cases and generalize well across complex variable interactions. The stepwise optimization approach ensured that the best-performing single classifier (DT) served as the baseline for ensemble modeling, leading to significant improvements in accuracy, sensitivity, and specificity.

These AI-based models' superior performance highlights their potential for practical implementation in clinical settings. Its higher sensitivity ensures that high-risk patients are accurately identified, allowing for timely interventions and improved patient safety. Meanwhile, its robust specificity minimizes false positives, reducing unnecessary resource allocation. Compared to traditional tools, the AI model’s dynamic learning capabilities and adaptability to complex data interactions address critical limitations, such as static variable selection and poor generalizability. These findings underscore the clinical utility of AI-driven models in enhancing fall risk assessment and streamlining decision-making processes in healthcare. These findings underscore the effectiveness of the AI-based model in predicting fall risk and its potential for integration into clinical decision support systems.

The model can complement existing fall assessment scales and clinical judgment, providing a more comprehensive and precise evaluation of individual fall risk by considering a broader range of factors and their interactions. Besides, healthcare providers can integrate this model into their electronic medical record of the Hospital information system (HIS), enabling real-time risk assessment to identify high-risk groups of inpatients for falls. Leveraging machine learning algorithms and predictive modeling, artificial intelligence (AI) can analyze extensive datasets, including patient demographics, medical history, medication records, laboratory results, and other relevant factors. In addition, AI models can continuously learn and adapt based on new data. This allows for ongoing refinement of the model's accuracy and performance over time, enhancing its effectiveness in identifying high-risk patients. For example, upon admission of a new patient, their data can be analyzed by the AI model to generate a risk score or classification indicating the likelihood of falls during their hospitalization. This integration of AI may facilitate timely and personalized interventions, improving patient safety and reducing fall-related incidents.

Limitations of the study

Regional data biases may exist due to variations in available medical resources across healthcare institutions, limiting the generalizability of the study findings. However, our findings have been compared with the existing literature which helped validate the accuracy and reliability of the study. To address potential inaccuracies and limitations in data quality associated with retrospective data from medical records, several measures were taken in this study. Multiple data sources were utilized, including medical records, prescription records, nursing notes, and fall assessment reports. This approach aimed to improve the reliability of the collected data by cross-validating information obtained from different systems. In addition, data cleaning and preprocessing procedures were rigorously implemented before analysis. Thorough efforts were made to address missing or erroneous data, resolve inconsistencies, and standardize variables. Furthermore, to mitigate bias in the machine learning algorithms, cost-sensitive learning and data resampling techniques were employed. These strategies were utilized to enhance the overall quality and integrity of the data, ensuring a more robust and reliable analysis.

Conclusion

Preventing patient falls is a paramount objective for healthcare organizations, and constructing a robust methodology to predict falls among high-risk patients is essential in mitigating these adverse outcomes. By proactively identifying those at risk through the medical system, interventions can be tailored to each patient’s specific needs, reducing the incidence of falls and associated injuries. However, it's important to note that interventions should be tailored to the individual's specific needs and circumstances. Based on the factors identified in this study, a multidisciplinary approach involving healthcare professionals, including physicians, nurses, physical therapists, occupational therapists, pharmacists, and nutritionists, can ensure a comprehensive and personalized intervention plan to address the identified risk factors and minimize the risk of falls.

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Conflicts of interest

All authors declare that they have no known conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The research data used to support the findings of this study are restricted by the Hospital Ethics and Compliance to protect patient confidentiality. Data are available from Chia-Lun Lo for researchers who meet the data access criteria.

Authors' Contributions Chia-Lun Lo, Hsiao-Yun Chang, Chiu-Hsiang Wu

Chia-Lun Lo & Chia-En Liu conceptualized the study, performed methodology, and prepared the original draft manuscript. Hsiao-Yun Chang & Chiu-Hsiang Wu wrote, reviewed, and edited the manuscript.

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Supplement file 1. Attributes in the fall prediction model among the selected variables

Attributes \ Scales	Fall assessments			AdaBoost+C4.5
	Morse	STRATIFY	Hendrich	Prediction model
1. Sex	×	×	✓	✓
2. Age	×	×	×	✓
3. Gait	✓	×	×	✓
4. Lower limb prosthesis	×	×	×	✓
5. Ambulatory aid	✓	×	×	✓
6. Malnutrition	×	×	×	✓
7. Muscle power	×	×	×	✓
8. Karnofsky performance scale	×	✓	✓	✓
9. Barthel index	×	×	×	✓
10. Coma scale	×	×	×	×
11. Consciousness	×	✓	✓	✓
12. Mental status	✓	×	✓	✓
13. Activities during falls	×	×	×	×
14. Visual impairment	×	✓	×	✓
15. Pollakiuria	×	✓	✓	✓
16. Diarrhea	×	✓	✓	✓
17. Anemia or orthostatic hypotension	×	×	×	✓
18. Weakness or dizziness	×	×	✓	✓
19. Sleep disorders	×	×	×	✓
20. Diabetes	×	×	×	×
21. Cancer	×	×	×	×
22. Cardiovascular disease	✓	×	×	✓
23. Neurological disorders	✓	×	×	✓
24. Stroke	✓	×	×	✓
25. Musculoskeletal disorders	✓	×	×	✓
26. Dementia	✓	×	×	✓
27. Depression	✓	×	✓	✓
28. Falls within a year	×	✓	×	✓
29. History of falls	✓	×	×	✓
30. Drug-related orthostatic hypotension	×	×	×	✓
31. Cardiovascular drugs	×	×	×	×
32. Sedatives/Hypnotics	×	×	✓	✓
33. Diuretics	×	×	×	✓
34. Anticoagulants	×	×	×	✓
35. Antihistamines	×	×	×	✓
36. Analgesics/Anesthetics	×	×	×	✓
37. Sedatives and psychotropic drugs	×	×	×	✓
38. Anticonvulsants	×	×	✓	✓

Attributes \ Scales	Fall assessments			AdaBoost+C4.5
	Morse	**STRATIFY**	**Hendrich**	**Prediction model**
39. Drug-induced risk of falls	×	×	×	✓
40. Departments	×	×	×	×
41. Nursing wards	×	×	×	×
42. Types of room	×	×	×	×
43. Protective restraint	×	×	×	×
44. Medical history	×	×	×	✓
45. Injuries caused by falls	×	×	×	×
46. Duration of hospitalization	×	×	×	×
47. Time of falls	×	×	×	×
48. Patient companion	×	×	×	✓
49. High-risk group of falls	✓	✓	✓	✓
50. Years of staff experience	×	×	×	×
51. Childbirth	×	×	×	×
52. Surgery	×	×	×	✓
53. Intravenous therapy	✓	×	×	✓

Supplement file 2. List of medications

Classification	Medications (Brand Name)
Sedatives/ Hypnotics	Estazolam（Eurodin®）
	Flunitrazepam （Modipanol®）
	Midazolam
	Zolpidem（Stilnox®）
	Zopiclone (Genclone®)
	Clonazepam（Clonopam®）
	Rivotril(Clonazepam®)
	Brotizolam (Lendormin®)
	Zaleplon （Sonimax®）
Sedatives/ Hypnotics	Estazolam（Eurodin®）
	Flunitrazepam （Modipanol®）
	Midazolam
	Zolpidem（Stilnox®）
	Zopiclone (Genclone®)
	Clonazepam（Clonopam®）
	Rivotril(Clonazepam®)
	Brotizolam (Lendormin®)
	Zaleplon （Sonimax®）
Drugs-induced orthostatic hypotension	Madopar®（Levadopa 200 + Benserazide 50）
	Sinemet® 125 mg/tab (C/L=100/25)
	Chlorpromazine（Winsumin®）
	Pentoxifyllin（Trental®）
	Amantadine（Dopadine®）
Cardiovascular drugs	Nifedipine (Adalat®)
	Nifedipine (Adalat®)
	Nifedipine (Adalat-oros®)
	Hydralazine（Esidri ®sct, Aprelazine®）
	Reserpine+Hydralazine+Esidrex（Esidri ®sct）
	Terazosin（Hytrin®）
	Alfuzosin HCl (Azosin SR®)
	Doxazosin XL (Doxaben XL®)
	Hydrochlorothiazide（Dithiazide®）
	Propranolol（Inderal ®10, 40）
	Metoprolol（Betaloc ZOK®）
	Atenolol（Ateol®）
	Atenolol（Tenormin®）
	Labetalol（Trandate®）
	Labetalol（Trandate®）
	Digoxin（LaNoXin®）
	Digoxin（Lanoxin®；Cardiacin elixir®）
Diuretics	Furosemide（Lasix® ）
	Furosemide（Rasitol®）
	Spironolactone（Aldactin®）
	Aspirin（AsPirin®）
	Aspirin（Bokey®）
	Heparin（HeParin®）
	Dipyridamole（Persantin®）
	Dipyridamole+ASA（Aggrenox®）
	Dipyridamole+ASA（Aggrenox®）
	Clopidogrel（Plavix®）
	Dabigatran（Pradaxa®）
Antihistamines	Chlorpheniramine（Oballercal®）
	Chlorpheniramine maleate Chlorpheniramine®）

Classification	Medications (Brand Name)
	Chlorpheniramine（Chlorpheniramine®；Coldex®）
	Acetaminophen+Salicylamide+Chlorpheniramine maleate+Caffein（Coldex cap ®）
	Cyproheptadine（Cypromin ®）
	Cyproheptadine（Cytadine®；Periactin®）
	Mebhydrolin（Meblin®；Incidal®）
Analgesics/ Anesthetics	Morphine 10 mg/tab
	Morphine HCl
	Morphine SO4 （Morphine SR®）
	Fentanyl（Fentanyl-FRESENIUS®）
	Fentanyl（Fentanyl®）
Sedative and psychotropic drugs	Lorazepam（Ativan®）
	Lorazepam（Anxicam®）
	Alprazolam（Xanax®）
	Clobazam（Frisium®）
	Bromazepam （LexoTan ®）
	Haloperidol (Haldolin)
	Haloperidol (Haldol)
	Haloperidol (Haldol)
	Diazepam（Diazepam®）
	Fludiazepam（Erispan®）
	Diazepam（Diazepam®）
	Imipramine（Tofranil®）
	Doxepin (Ichderm)
	Sulpiride（Sopid®）
Anticonvulsants	Amantadine（Dopadine®）
	Biperiden（bipiden ®）
	Biperiden（bipiden ®）
	Bromocriptine（butin®）
	Rifabutin（Mycobutin®）
	Carbamazepine（Tegretol ®）
	Carbamazepine（Tegretol CR-FCT ®）
	Clonazepam（Clonopam ®）
	Entacapone（Comtan ®）
	Gabapentin（Neurontin ®）
	Lamotrigine（Lamictal ®）
	Levetiracetam（Keppra ®）
	Levetiracetam（Keppra ®）
	Levadopa 200 + Benserazide 50（Madopar ®）
	MAGNESIUM SULFATE（Magnesium Sulfate ®）
	Oxcarbazepine（Trileptal ®）
	Oxcarbazepine（Trileptal ®）
	Phenytoin（dilantin ®）
	Phenytoin（Aleviatin ；dilantin ®）
	Pramipexole（Mirapex®）
	Topiramate（TopaMax ®）
	Valproate.Na （depakine ®）
	depakine 400mg/vial