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A Prediction Algorithm for Fall Risk Assessment among Community-Dwelling Elderly People

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Abstract **–** Worldwide, life expectancy has steadily increased over the years. However, the integrity and the functionality of physiological systems reduce over time making older people more vulnerable to adverse events such as falls. Consequences of falls can include physical injuries (hip fractures), psychological issues (fear of falling) and social isolation (need for assistance) increasing the demand for healthcare services (hospitalization, rehabilitation, institutionalization). Despite many studies investigated the most predisposing factors to a fall risk, this study aimed at identifying those factors through a multidimensional health assessment of elderly people crossing over multiple health domains such as nutritional, clinical, psychological, social, and functional. The acquired variables were processed in terms of data cleaning and coding, to make them ready for subsequent statistical evaluation. Correlation and regression analyses were performed to find out the relevance of the variables with respect to the fall event. The most significant variables were accounted for the development of the predictive index. Each predictor was associated with a score according to specific weights so that the sum of the answers to each question of the index gave the final fall risk index. Its validation was assessed over the sample of the study by comparing the index output to that of the multidimensional evaluation and the one of a common fall risk test. Clinicians will benefit from this tool for a fast and easy screening of fall risk among community-dwelling seniors to act promptly on those subjects at increased risk, and preventively on low-risk subjects. This way, it is possible to optimize time, costs, and resources for sustainable and effective management of patient care.

Keywords**:** Data-driven approach, Risk assessment, Risk prediction, Older adults, Predictive algorithm, Fall-risk detection

1. Introduction

Worldwide, life expectancy has steadily increased over the years. The number of persons aged 80 years or older is expected to triple between 2020 and 2050 to reach 426 million [1]. However, the integrity and the functionality of physiological systems reduce over time, making older people more vulnerable to adverse events such as falls. Fall is defined as "an event in which a person accidentally lies on the ground or at another lower level unaware of the loss of consciousness" [2]. In 2018, about 30% of US elders (≥65 years) reported at least one fall in the past year, and about 10% reported a fall-related injury [3]. Falls are crucial in the worsening of functional independence of elderly people and their quality of life. The most direct consequences include physical injuries (e.g., hip fractures), disability and death [4]. Beside this, psychological issues (fear of falling), social isolation (need for assistance) and increased demand for healthcare services (hospitalization, rehabilitation, institutionalization) are not trivial. According to the Center for Disease Control and Prevention, in 2020, 36,508 older adults aged 65 and older died from preventable falls, and over 2.8 million were treated in emergency departments. Falls deaths and emergency departments visits have increased over the past 10 years by 59% and 19%, respectively. The best way to address this issue is to adopt a preventive strategy focused on the improvement of the elder's lifestyle. Through evidence-based falls prevention programs the risk of falls among seniors can be substantially reduced [5]. Fall risk assessment is usually performed after the onset of health problems that affect gait and postural stability. The majority of screening programs to identify people at risk of falls are based on the evaluation of mobility-related aspects such as gait parameters, and balance performance, underestimating environmental, social, cardiological, nutritional, and psychological factors that can make elderly people more susceptible to adverse events. This results in inaccurate and time-consuming physical domain investigations. Moreover, these clinical tests are conducted in specialized centres by clinical experts through the performance of multiple tasks resulting in time consuming evaluations. The most common assessments include Tinetti performance Oriented Mobility Assessment (POMA) [6], Berg Balance Scale (BBS) [7], Dynamic Gait Index [8], and Timed Up and Go (TUG) [9]. Among them, TUG is widely used since it is easy to perform, low time cost, and reliable. It requires a subject to stand up, walk 3 meters, turn back and sit down. The duration of the whole execution is correlated to the level of mobility. Additional tools have been developed to assess the fall risk based on anamnestic data or screening information discarding a functional assessment. The Downton Fall Risk Index predicts the fall risk based on 11 items (previous falls, medication, sensory deficits, mental state and gait quality). However, it is more indicated for elderly people in continuing care wards and residential facilities [10]. The St. Thomas Risk Assessment Tool in Falling elderly inpatients (STRATIFY) [11] is specific for hospitalized patients and assesses the fall risk based on 5 items including past history of falling, patient agitation, visual impairment, incontinence, transfer and mobility. Chen et al. [12] developed an instrument for the assessment of the risk of falling in Taiwan older adults based on eight risk factors (female sex, living alone, incontinence, perceived unhealthiness, perceived pain, hospital admission in the past year, low activities of daily living (ADL) scores, and low mobility function scores). However, it requires the execution of mobility tests and the administration of ADL questionnaires prolonging the computation time.

This work is based on an Italian National Project (MOSAICO) funded by Ministry of Economic Development and Marche Region under the grant agreement for innovation. MOSAICO aims at developing a new assistance model to improve the quality of life of elderly people by conjugating social- and health-care services through personalised paths. The main purpose is to promote an active and independent living of elderly by preventing the onset of acute events such as falls.

In this context, the present work aims at exploring the fall risk factors affecting the elderly and at developing a fall risk index specific for community-dwelling elderly people by investigating multiple aspects of the health. Such a predictive system can help general practitioners easily and early identify elderly people at risk of fall to adopt prompt patient-specific intervention to improve their life quality preventing any further worsening of the health. Indeed, based on the fall risk score ICT devices could be assigned to at risk elderly people to monitor vital sign and detect any adverse event. Moreover, by computing such a simple fall risk score elderly people could become aware of their health status and be more prone to assume better lifestyles to reduce the risk.

2. Methods

The current study aims to develop a fall risk index for elderly people according to the methodology shown in Figure 1.

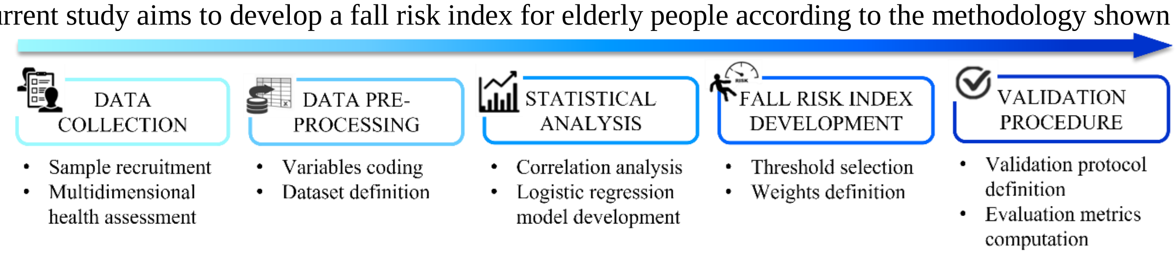

Figure 1: Workflow for the development of the fall risk index

First, data about community-dwelling elderly people are collected in a multidimensional health assessment. The multidisciplinary staff of clinical and social operators converges on a decision to classify people at risk of fall. All the gathered data are then processed to prepare the dataset for subsequent statistical analysis. Data are cleaned and coded in a standardised format, according to the nature of the acquired variables. Following, two key points of the work are the development of a logistic regression analysis for the identification of the fall risk predictor variables, and the index scoring criteria. To conclude a validation protocol is defined to assess the reliability and efficacy of the developed fall risk index.

2.1. Data Collection

The target population involved community-dwelling elderly subjects enrolled by their general practitioner according to the following inclusion criteria: (i) subjects aged 75 years or older, (ii) residency in small municipalities (< 5000 inhabitants) of the seismic crater areas of Marche Region in the provinces of Fermo and Macerata (Italy), (iii) levels 1, 2, 3 of the Modified Rankin Scale, which means a good-to-moderate level of autonomy. The presence of comorbidities did not represent an exclusion criterion. Respondents were excluded if they experienced any severe cognitive impairment since most of the collected variables were assessed through anamnestic interviews. Eligible older adults signed their written informed consent to participate in this study.

Participants' health was evaluated through an extended multidimensional assessment by a team of social and clinical operators as described in [13]. The elderly's health status was investigated through face-to-face interview based on structured and validated questionnaires and clinical exams to collect socio-demographic data, anthropometric measures, information about functional independence in the ADL, mobility and equilibrium data, mood disorders, and clinical information. The acquired variables were collected in the software platform MOSAICO according to the GDPR Regulation (EU) 2016/679 and Legislative Decree 196/2003 for privacy and confidentiality issues.

2.2. Data pre-processing

A missing at random mechanism characterised the collected data with no obvious patterns across variables and participants. Variables presenting frequently missing in the dataset were discarded, as well as samples with multiple missing values. Data imputation was not performed to avoid introducing bias in the model.

The dataset to be used in subsequent statistical analysis was defined based on the nature of the acquired variables. Binary values were used to code dichotomous variables (i.e., gender, living alone, environmental barriers, gait disorders, limited range of motion (ROM), hypertension, orthostatic hypotension, diabetes, hypercholesterolemia, previous syncope, exertional dyspnoea, hearing and visual impairments, depression, neurological deficit, nycturia, previous falls, walking aids use) so that the presence of a deficit was coded as 1. Age, weight, height, BMI, Modified Barthel Index (MBI), BBS, and TUG were handled as continuous variables due to their numerical nature.

2.3. Statistical analysis

This step focuses on the methodology to identify the most predisposing risk factors for fall events to develop a classification risk score.

A descriptive analysis was performed for each variable for a general description of the study sample. In particular, the continuous variables were examined by means and standard deviation (SD), and categorical variables were described using frequencies and percentages. A logistic regression approach was then used to select the fall risk predictor variables. The dependent variable for the logistic regression analysis was the presence of previous falls.

Despite each collected variable could be a candidate predictor, the full model approach, in which all predictors are included in the model irrespective of their association with the outcome, is discarded. Indeed, a rule of thumb recommends a minimum of 10 events (positive outcome) per predictor variable included in the model to reduce the bias. Given the limited sample size and the larger number of variables, a binomial logistic regression model is developed according to a backward elimination approach. The least significant variables (p-value<0.2) are sequentially removed from the model. The stopping rule is satisfied when all remaining variables in the model have a p-value smaller than 0.1 and the removal of additional variables induced an increase in the Akaike Index Criterion (AIC). With respect to forward selection, this approach has the advantage of considering the effects of all variables simultaneously and is more generalizable [14].

However, to avoid collinearity problems, a correlation analysis was done between the candidate predictors, prior to the logistic regression model development. The Pearson and Spearman correlation coefficients allowed evaluating the correlation between continuous variables. P values less than 0.01 were considered statistically significant. The Chi-square was used to test the association between dichotomous variables. The effect size of the association was assessed through Cramer's V value. If Chi-square test assumptions were violated (expected frequency counts are <5) Fisher's test was used. The correlation between continuous and categorical variables was assessed through a binomial logistic regression. Highly correlated variables were discarded from the logistic regression analysis.

The open-source software Jamovi, version 2.3.18.0 [15] was used to carry out data analyses.

2.4. Fall risk index development

In order to develop a fall risk assessment tool, the acquired variables were analysed via logistic regression, and regression coefficients were calculated to quantify the contribution of each predictor to the outcome risk estimation. According to the logistic regression analysis, the patient's predicted probability of falls is computed through equation (1) and equation (2).

$$\mathrm{P(y = 1)} = \frac{e^{logit(P(y=1))}}{1 + e^{logit(P(y=1))}} \tag{1}$$

$$\mathrm{logit(P(y = 1))} = \beta 0 + \beta 1 * \mathrm{x1} + \mathrm{b2} * \mathrm{x2} + \cdots \mathrm{bn} * \mathrm{xn} \tag{2}$$

where β are the regression coefficients and xn the n independent variables.

Due to the screening application of the index, that is to identify people at risk of fall, the cut-off value was determined based on the receiver operating characteristic (ROC) curve that describes the relationship between sensitivity and false positive rate (1-specificity).

A weighted risk score was then obtained based on the regression coefficient values by rounding off the values of the beta coefficient to the nearest integer [16].

2.5. Validation

The classification model performance was assessed in terms of sensitivity, specificity, accuracy, and area under the ROC curve (AUC). As for this latter, a value of 1 means perfect prediction at a defined threshold and 0.5 represents independence of the event. Values >0.70 are generally considered to be useful.

For the purposes of our study, sensitivity was defined as the proportion of fallers who were correctly classified. Specificity was defined as the proportion of non-fallers among those who actually do not have the event. The accuracy enabled evaluating how many observations, both positive and negative, were correctly classified. By computing the value of the fall risk index validation and reliability were assessed over the sample of the study by comparing its output to that of the multidimensional evaluation of healthcare operators, and of a common test (TUG) to assess the fall risk [17-19]. A cut-off of 12 s was assumed as threshold for fall risk [20]. To this aim false positives and false negatives allowed evaluating the index misclassification with respect to the above-mentioned control metric. False positives (FP) refer to participants the index classified at risk of fall contrary to the clinicians' diagnosis. False negatives (FN) refer to participants judged at risk of fall by the clinicians that the index misclassified.

It was not possible to assess the number of people who fell at one-year monitoring due to the unavailability of data (recall bias, death, and sanitary residence care).

3. Results and Discussion

3.1. Descriptive statistics

Table 1 gives the basic information of all participants in the study. Of 120 eligible elderly people 48 were male (mean age 81 years), 72 were females (mean age 82 years). Among the eligible participants, 43% (n=51) presented a history of previous falls.

Table 1: Study sample's characteristics

Characteristics	**Mean±SD/ Counts (%) (N=120)**	**Characteristics**	**Counts (%) (N=120)**
Age (years)	81.4±5.4	Limited ROM[2](Yes)	46 (38%)
Modifies Barthel Index (MBI)	98±5.6	Neurological deficits[3] (Yes)	23 (19%)
Berg Balance Scale (BBS)	49±9.4	Environmental Barriers[4] (Yes)	67 (56%)

TUG	15±8.4	Hypertension (Yes)	113 (94%)
Weight (Kg)	70.2±11.6	Diabetes (Yes)	26 (22%)
Height	1.57±0.1	Hypercholesterolemia (Yes)	61 (51%)
BMI (kg/m^2)	28.4±4.5	Previous syncope (Yes)	17 (14%)
Gender (Male)	48 (40%)	Depression (Yes)	22 (18%)
Previous falls (Yes)	51 (43%)	Nycturia (Yes)	67 (56%)
Living Status (alone)	64 (53%)	Visual Impairments (Yes)	59 (49%)
Walking aids[1] (Yes)	22 (18%)	Hearing loss (Yes)	42 (35%)
Orthostatic hypotension (Yes)	35 (29%)	Gait disorders (Yes)	52 (43%)
Exertional dyspnoea (Yes)	22 (18%)		

[1]Any device designed to assist walking or otherwise improve the mobility of people (e.g., canes, crutches, walkers). [2]It means a limitation in the range of motion (e.g., flexion/extension, abduction/adduction, internal/external rotation, plantar flexion/dorsiflexion) of lower limbs (hip, knee, ankle, foot). [3]Neurological deficits include problems related to musculoskeletal system by assessing muscle tone, hypoesthesia, muscle weakness, muscle trophy and sensitivity (tactile and painful). [4]It refers to the presence of stairs in the house without lift.

3.1. Multivariate Analysis

The classification model was developed according to the procedure represented in Figure 2.

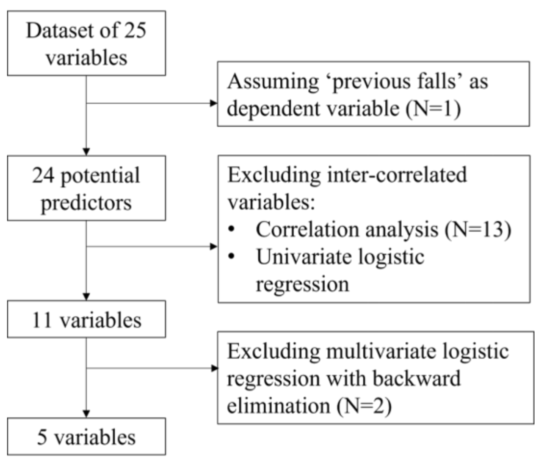

Figure 2: Variable selection procedure

The dependent variable to be used in the final logistic regression model was ‘previous falls’. Of all the acquired variables (Figure 2) an initial selection was made according to the correlation between candidate predictors.

It appears a strong correlation between TUG and BBS (rho=-0.749, p<.001), weight and BMI (rho=0.739, p<.001), Walking aids-MBI (<.001), Walking aids-TUG (<.001), Walking aids-BBS (<.001), Walking aids-Age (0.001), Walking aids-Height (<.001), Gender-TUG (<.001), Gender-BBS (<.001), Gender-Weight (<.001), Gender-Height (<.001), Neurological deficits-MBI (0.003), Neurological deficits-TUG (0.01), Neurological deficits-BBS (0.007), Depression-Height (0.005), Gait disorders-MBI (0.009), Gait disorders-TUG (<.001), Gait disorders-BBS (<.001), Gait disorders-Age (0.002), Gait disorders-Height (0.001), Gait disorders- BMI (0.007), Exertional Dyspnoea-BMI (0.003). A moderate correlation occurs between TUG and height (rho=-0.443, p<.001), MBI and TUG (rho=-0.527, p<.001), MBI and BBS (rho= 0.470, p<.001), BBS and Age (rho=-0.402, p<.001), BBS and height (rho= 0.432, p<.001), weight and height (rho= 0.467, p<.001), Walking aids and gait disorders (X2 (N=120, df=1) = 20.3, p<.001, Cramer’s V= 0.41), walking aids and gender

(X2 (N=120, df=1) = 14.1, p<.001, Cramer's V= 0.343), limited ROM and visual Impairments (X2 (N=120, df=1) = 12.4, p<.001, Cramer's V= 0.318), previous syncope and orthostatic hypotension (X2 (N=120, df=1) = 12.1, p<.001, Cramer's V= 0.322), neurological deficits and gait disorders (X2 (N=120, df=1) = 10.8, p<.001, Cramer's V= 0.300), hypercholesterolemia and exertional dyspnoea (X2 (N=120, df=1) = 10.3, p=0.001, Cramer's V= 0.294), visual impairments and gait disorders (X2 (N=120, df=1) = 9.66, p=0.002, Cramer's V= 0.284), living alone and diabetes (X2 (N=120, df=1) = 6.79, p=0.009, Cramer's V= 0.238), and exertional dyspnoea and gait disorders (X2 (N=120, df=1) = 6.77, p=0.009, Cramer's V= 0.238).

The selection between highly correlated variables was based on their correlation with respect to the outcome variable "previous falls", thus, candidate predictors with the highest p-value were discarded [14]. After a first variable selection a backward elimination procedure was applied to the model characterized by the following variables: gender, limited ROM, previous syncope, diabetes, environmental barriers, gait disorders, nycturia, depression, hearing loss, hypertension, and hypercholesterolemia.

Table 2 reports the final logistic regression model.

Table 2: Multivariable fall risk logistic regression analysis of selected predictors

Predictor	**Estimate**	**SE**	**p**	**Odds ratio (95% Confidence Interval)**
Intercept	-1.681	0.504	<.001	0.186 (0.0693-0.500)
Limited ROM	0.780	0.434	0.072	2.182 (0.9313-5.112)
Gender	1.631	0.475	<.001	5.111 (2.0145-12.966)
Previous syncope	1.757	0.672	0.009	5.797 (1.5546-21.620)
Environmental barriers	-0.711	0.431	0.099	0.491 (0.2109-1.144)
Diabetes	0.902	0.534	0.091	2.464 (0.8653-7.017)

Estimates represent the log odds of "Previous falls=1" vs. "Previous falls=0"

Variables more associated with a fall include the following categorical variables: being female (the odds ratio for falling in women was 5.1, 95% CI 2.01-12.97), having had a previous episode of syncope (OR 5.8, 95% CI 1.55-21.62), having a limited ROM at lower limbs (OR 2.2, 95% CI 0.93-5.11), having diabetes (OR 2.5, 95% CI 0.87-7.02). There is evidence that female gender is a strong fall risk predictor [21, 22]. Indeed, as a consequence of menopause women experience a fast reduction in bone mineral density making them more susceptible to osteoporosis, falls, and fractures [23]. Syncope is defined as s a temporary loss of consciousness and postural tone that can lead to unexplained falls. About 20% of cardiovascular syncope in patients older than 70 appears as a fall [24]. Despite being an association between syncope and falls, the literature reports a low percentage of syncope-related falls (0.3-5%). Indeed, many clinical studies exclude patients with a history of syncope because of the higher risk of hospitalization. Moreover, underestimation of syncope-related falls can be suggested due to the retrograde amnesia for the loss of consciousness [24]. Concerning the 'diabetes' predictor, many studies confirm that older adults with diabetes mellitus are associated with greater risk of fall [25]. Declines in sensory function caused by diabetes-induced neuropathy or retinopathy may lead to an increased risk of falls [26]. Hypoglycemic symptoms are highly correlated with falls. In the study of [27] lower extremities active ROM was found to be significantly associated with the risk of falls in older adults in univariate analysis. Jung et al. [28] assessed that reduced hip flexion, hip external rotation and ankle dorsiflexion ROMs are important risk factors for falls in older women.

According to the developed fall risk classification model, the probability of falling decreases in presence of environmental barriers at home (OR 0.5, 95% CI 0.21-1.14). Despite evidence suggests stairs as a hazard for falls, the model's outcome can be explained by the fact that going up the stairs improves the muscle tone and contribute to the maintenance of the functional capacity. Indeed, among the elderly people who have environmental barriers at home (N=67), 60% had a normal gait without any problem and 63% did not present any limitation in the range of motion. Moreover, Tomioka et al. [29] found out that women who lived in walk-up residences had a lower risk for IADL decline (OR = 0.72, 95% CI = 0.52–0.99).

It is worth noting that this study assumed as environmental barriers the presence of stairs inside a house discarding further barriers such as carpets, slippery surfaces, inadequate lighting that can affect the carefulness of individuals. Thus, further investigation is recommended.

A cut-off of 33% was selected on the ROC curve as a trade-off between high sensitivity for screening purposes and adequate specificity, allowed to obtain a sensitivity of 73% and a specificity of 67%. The model accuracy is 0. 692, and the area under the ROC curve is 0.756.

Equations 1 and 2 were used to predict the fall risk for each patient. 60 elderly people resulted to be at risk of fall with respect to the 54 individuals judged at risk according to the clinicians.

In order to develop an instrument for easy and fast screening of fall risk, a score was computed by assigning a weight to each fall predictor, based on the regression coefficients. Table 3 reports the developed fall risk index.

Table 3: Fall risk index scoring system

Item	**Weight**	**Score**
Gender	2	1 if gender=female, 0 if male
Previous syncope	2	1 in presence of past syncope otherwise 0
Limited ROM	1	1 in case of limited ROM at lower limbs, otherwise 0
Environmental barriers	-1	1 in presence of environmental barriers at home, otherwise 0
Diabetes	1	1 in case of diabetes, otherwise 0

The final prediction score is given by the sum of each item's score multiplied by the respective weight. The higher the score the greater the risk of experiencing a fall. The minimum score would be attributed to a non-diabetic male older adult without a history of previous syncope, with perfect mobility in the lower limbs and presence of stairs at home.

3.1. Validation

A mean score of 1.52 is obtained by computing the developed fall risk index for each participant in the study. The mode is 2. According to this index and the above-mentioned threshold 50% of the sample study (N=60) results at risk of fall. The sensitivity of the index is 78%, whilst the specificity is 72%. The model is able to correctly classify into the correct class the 75% of the observations. A comparison between the outcome of the index and one of two control metrics (clinicians' decision and TUG) presented in section 2.5 is reported in Table 4.

Table 4: Fall risk index validation results

	Participants at risk of fall	**Matching**	**FP**	**FN**
Clinical evaluation	54 (45%)	80 (67%)	23 (19%)	17 (14%)
TUG	63 (53%)	79 (66%)	19 (16%)	22 (18%)

These findings reveal that the fall risk index predictions are quite in agreement with the ones provided by the clinicians during the multidimensional health assessment and TUG test. The performance of the fall risk index can be improved by overcoming some limitations of the study. The major one is related to the limited sample size that determined a selection procedure of the variables to be included in the model reducing the number of candidate predictors. By extending the number of enrolled elderly people it will be possible to investigate the incidence of multiple health aspects not necessarily related to gait and balance field on the fall risk. Moreover, since the population study involved community-dwelling individuals, the collected information, including the outcome variable, was dependent on the patient's memory which could be prone to recall bias. Moreover, the sample study is representative of the community-dwelling seniors populating the inner areas of Marche region compromising the generalization ability of the algorithm to adapt to new data.

4. Conclusion

This paper proposes a fall risk predictive index that helps clinicians identify elders at risk of fall in a fast and easy way as a daily routine service. The procedure is based on the investigation of multiple aspects of the elders' health, not limited to the functional and mobility domain, for more accurate identification of fall risk factors. A feature selection procedure based on correlation and logistic regression analyses allowed defining a classification model including five simple dichotomous variables (gender, previous syncope, limited ROM, environmental barriers, diabetes). The index was conceived as a linear combination of weights, based on the regression coefficients, and scores of the categorical variables. The sensitivity of the index is 78%, whilst the specificity 72%. Its predictive performance was compared to the ones of clinicians and TUG test. Results are encouraging, despite some misclassifications occurred. A larger and more heterogeneous cohort to be split into training and validation could improve the algorithm's reliability and efficacy. This tool could be adopted by general practitioners to stratify their patients based on their risk of falling. Elderly people could be made aware of their risk and encouraged to adopt healthier lifestyles in a preventive way.

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