JAMDA xxx (2017) 1–6

JAMDA

journal homepage: www.jamda.com

Original Study

A Simple Algorithm to Predict Falls in Primary Care Patients Aged 65 to 74 Years: The International Mobility in Aging Study

Fernando Gomez MD [a,*], Yan Yan Wu MA, PhD [b], Mohammad Auais PT, PhD [c], Afshin Vafaei PhD [d], Maria-Victoria Zunzunegui PhD [e]

[a] Research Group on Geriatrics and Gerontology, Faculty of Health Sciences, Universidad de Caldas, Manizales, Colombia
[b] Office of Public Health Studies, University of Hawaii at Mānoa, Honolulu, HI
[c] School of Rehabilitation Therapy, Queen's University, Kingston, Ontario, Canada
[d] Department of Public Health Sciences, Queen's University, Kingston, Canada
[e] Research Institute of Public Health of the Université de Montréal (IRSPUM), Montreal, Canada

Keywords:
Accidental falls
risk factors
logistic regression tree
older adults

A B S T R A C T

Objective: Primary care practitioners need simple algorithms to identify older adults at higher risks of falling. Classification and regression tree (CaRT) analyses are useful tools for identification of clinical predictors of falls.
Design: Prospective cohort.
Setting: Community-dwelling older adults at 5 diverse sites: Tirana (Albania), Natal (Brazil), Manizales (Colombia), Kingston (Ontario, Canada), and Saint-Hyacinthe (Quebec, Canada).
Participants: In 2012, 2002 participants aged 65–74 years from 5 international sites were assessed in the International Mobility in Aging Study. In 2014 follow-up, 86% of the participants ($n = 1718$) were reassessed.
Measurements: These risk factors for the occurrence of falls in 2014 were selected based on relevant literature and were entered into the CaRT as measured at baseline in 2012: age, sex, body mass index, multimorbidity, cognitive deficit, depression, number of falls in the past 12 months, fear of falling (FoF) categories, and timed chair-rises, balance, and gait.
Results: The 1-year prevalence of falls in 2014 was 26.9%. CaRT procedure identified 3 subgroups based on reported number of falls in 2012 (none, 1, ≥2). The 2014 prevalence of falls in these 3 subgroups was 20%, 30%, and 50%, respectively. The "no fall" subgroup was split using FoF: 30% of the high FoF category (score >27) vs 20% of low and moderate FoF categories (scores: 16–27) experienced a fall in 2014. Those with multiple falls were split by their speed in the chair-rise test: 56% of the slow category (>16.7 seconds) and the fast category (<11.2 seconds) had falls vs 28% in the intermediate group (between 11.2 and 16.7 seconds). No additional variables entered into the decision tree.
Conclusions: Three simple indicators: FoF, number of previous falls, and time of chair rise could identify those with more than 50% probability of falling.

Falls in older adult populations represent a major problem in general practice because of their high prevalence, multiple risk factors, and considerable negative health consequences (morbidity, mortality, loss of autonomy, and institutionalization).[1,2] Falling is a geriatric syndrome because of its complex etiology that involves interactions between 2 or more independent diseases or between accumulated effects of and age-related impairments in multiple systems.[3] At least 400 risk factors are reported to be attributable to the occurrence of falls[4]; however, only several risk factors are consistently identified in longitudinal studies. These include polypharmacy, previous falls, dizziness, and poor muscle strength, gait, and balance.[5–8]

A proper management of falls in primary care warrants examining all potential risk factors, relationships between them, and possible interactions between the myriad of potential risk factors.[3,6] Furthermore, recurrent falls may have different risk factors and mechanisms[9,10] and some risk factors may be more relevant to specific

This work was supported by a grant from the Canadian Institutes of Health Research (CIHR), grant number 108751.

The authors declare no conflicts of interest.

* Address correspondence to Fernando Gomez, MD, Research Group on Geriatrics and Gerontology, Faculty of Health Sciences, Universidad de Caldas, Manizales, Colombia.
E-mail address: gomez.montes@ucaldas.edu.co (F. Gomez).

http://dx.doi.org/10.1016/j.jamda.2017.03.021
1525-8610/© 2017 AMDA – The Society for Post-Acute and Long-Term Care Medicine.

subpopulations. For example, activities of daily living limitation is a stronger risk factor for those with a positive fall history and age is a more important risk factor for men.[11]

Most risk factors for falling studies use a prospective observational design for the identification of pertinent risk factors. These epidemiologic designs provide relatively strong evidence; however, methodological challenges surrounding them including loss to follow-up, change in the exposure status during follow up, and the possibility of recurrent events for the same person, may bias the results.[12] Traditional analytic approaches such as logistic regression models are the most commonly used methods for simultaneous analysis of the influence of 1 or several risk factors on falls. However, systematic identification of "at-risk subpopulations" based on combination of multiple risk factors for falling is less common.[12] Classification and regression tree (CaRT) analysis is a valuable tool to guide researchers to reduce gaps in the application of evidence into practice. By simultaneous process of large numbers of predictor variables, CaRT provides individual values for quantification of the importance of each individual predictor.[13] Furthermore, this method is useful for the exploration of relationships between independent variables that is not easily achievable by traditional linear regression analyses.[14] Other clinical utility of CaRT is its ability to develop models for the evaluation of care, stratification of risks, and determination of prognosis.[15]

Although similar regression tree-based methods have been used to identify high-risk subgroups in large population studies [9,10,16–20] and hospital patients,[21] to the best of our knowledge they have not been applied to investigate falls risk factors in longitudinal studies of community-dwelling older people. Therefore, the aim of this study was to develop an algorithm to predict the risk of falling in primary care patients from different cultural and social backgrounds using a CaRT method.

Methods

Participants

The International Mobility in Aging Study is a population-based prospective cohort study designed to understand how life-course factors affect mobility of community-dwelling older adults. Participants come from 5 international sites: Tirana (Albania), Natal (Brazil), Manizales (Colombia), Kingston (Ontario, Canada), and Saint-Hyacinthe (Quebec, Canada). These cities represent diverse living standards in very different societies. Tirana is the capital of Albania, an ex-communist country with a high percentage of Muslim population in rapid transition to capitalism; Kingston is an university city in Ontario, and Saint-Hyacinthe is an agricultural center in Quebec; Manizales is located in the Andean coffee growing region, a relatively wealthy area of Colombia; and Natal is a coastal city and capital of a fairly poor region of North Eastern Brazil. Rationale for the International Mobility in Aging Study and detailed methodology has been described in previous publications.[22,23] Briefly, the sample includes 400 community-dwelling adults (200 men and 200 women) aged 65– 74 years at each site with a total sample size of 2000. Participants were recruited randomly from patient lists of primary care providers. Baseline data collection took place in 2012 and included 2002 participants aged 65–74 years, and the first planned follow-up was conducted in 2014. During these 2 years, 58 deaths occurred and 226 were lost to follow-up, leaving a sample size of 1718 representing a retention rate of 86%. The study received approvals from local ethics boards at the respective sites, and all participants signed an informed consent form. At the initial recruitment the Leganes Cognitive Test (LCT) was used to screen general cognitive levels of participants. Those with 4 errors in the orientation subscale were excluded.[24] We further excluded 56 participants with missing values. This left a final sample size of 1662 for analysis.

Definition of Falls

Fall was defined as "an unexpected event in which the participant comes to rest on the ground, floor, or a lower level"[25] and in this study was assessed retrospectively. We first asked participants whether they experienced a fall in the last 12 months and subsequent questions prompted the number of falls during the defined period. A recurrent faller was defined as any participant with at least 2 falls within the previous 12 months. We defined injurious falls if medical care was requires after the fall.

Risk Factors for Falling

The selection of falls predictors was based on relevant literature.[5–8] Potential predictors included demographic factors of age and sex and individual risk factors of fear of falling, number of chronic conditions, medication use, body composition, cognitive function, depression, physical performance, fall history, and mobility disability.

Fear of falling (FoF) was evaluated using the validated Falls Efficacy Scale-International. The instrument includes 16 questions about concerns for falling using a 4-point Likert scale (1– "not at all concerned" to 4– "very concerned")[26] with a possible range between 16 and 64 and higher scores indicative of greater concern. Using these scores, we defined 3 levels of FoF: "no/low (16–19)," "moderate (20–27)," and "high (>27)."[27]

Chronic conditions were documented based on self-report of medical conditions diagnosed by a physician. Eight medical conditions were included: hypertension, heart diseases, diabetes, cancer, chronic respiratory disease, stroke, arthritis, and osteoporosis. We also asked the participants whether they took any prescribed or over-the-counter medications in the past 2 weeks. Body mass index was calculated by dividing participants' weight (kg) by the square height (m^2) obtained from direct measurements.

The LCT, originally developed as a dementia screening test adapted to low-educated populations,[28] was used to assess participants' cognitive function. Higher scores (range: 0–32) of LCT represents a better cognitive function and a score of 22 or lower is indicative of dementia.[24] We used the 20-item self-reported Center for Epidemiologic Studies Depression Scale to assess depressive symptoms experienced over the preceding week.[29] Scores range from 0 to 60. In this study, we defined clinically relevant depression as having a Center for Epidemiologic Studies Depression Scale score of $\geq$16.[30]

Physical performance was assessed by the Short Physical Performance Battery (SPPB).[31] SPPB includes 3 timed tests of lower body function: a hierarchical test of standing balance, a 4-m walk, and 5 repeated chair stands. Each SPPB component is scored from 0 to 4 with a score of 0 representing inability to perform the test, and a score of 4 representing the highest level of performance. For the balance task, the participants are first asked to maintain their feet in side by side, followed by semi-tandem (heel of 1 foot alongside the big toe of the other foot), and then in tandem (heel of 1 foot directly in front of the other foot) positions for 10 seconds each. For gait speed, a 4-m walk at the participants' usual pace was timed. The test was repeated twice with the faster of the 2 tests recorded. Participants were asked to stand up and sit down 5 times as quickly as possible with their arms folded across their chests for the last component of SPPB. This was done only after participants first demonstrated the ability to rise once.

Mobility disability was defined as the self-reported difficulty in walking 400 m or climbing a flight of stairs without resting.[32] Activities of daily living disability was assessed by inquiring about difficulties in performing daily activities of toileting, bathing, dressing, getting out of bed, and walking across a small room.[33]

Statistical Analysis

Overall characteristics of the cohort as well as by fall status in 2014 were summarized by descriptive statistics. We used χ^2 tests to identify those risk factors that were significantly associated with the occurrence of falls. Then, recursive partition (or classification) tree analysis with the χ^2 Automatic Interaction Detection (CHAID) algorithm was performed to identify fall risk subgroups.[34,35]

CHAID is a classification method for building decision trees by using χ^2 statistics through the identification of optimal multiway splits. CHAID identifies a set of characteristics that best differentiates individuals based on a categorical outcome and creates exhaustive and mutually exclusive subgroups of individuals. It chooses the best partition on the basis of statistical significance and uses the Bonferroni adjusted *P* values to determine significance with a predetermined minimum size of end nodes. We used 5% Bonferroni adjusted *P* value and a minimum size of end nodes (n = 30) as the stopping criteria. Furthermore, 10-fold cross-validation method was applied to test tree stabilities.[36]

In the next step, multiple logistic regression analyses were conducted to estimate the effects of all risk factors. To compare the effectiveness of CHAID with multiple logistic regression methods, we calculated the odds ratios (ORs) for falls at each CHAID end nodes as well as the ORs for all risk factors obtained from multiple logistic regression models. Forest plot was used to visualize the ORs. Additional model fitting statistics such as accuracy, sensitivity, specificity positive predictive value (PPV) and negative predictive value (NPV) were also calculated for both CHAID and logistics regression. Statistical software of SPSS v 23.0 (SPSS, Inc, Chicago, IL) and R v 3.1.2 were used for the analysis.

Table 1
Sample Characteristics and Comparisons of Fall Status (n = 1662)

Sample Characteristics	Total Population n = 1662	Fall n = 449 (27%)	No Fall n = 1213 (73%)	*P* Value*
Age group				
64–69	930 (56.0)	257 (27.6)	673 (72.4)	.56
70–75	732 (44.0)	192 (26.2)	540 (73.8)	
Sex				
Male	785 (47.2)	189 (24.1)	596 (75.9)	.01
Female	877 (52.8)	260 (29.6)	617 (70.4)	
Number of falls last year				
0	1,206 (72.6)	263 (21.8)	943 (78.2)	<.001
1	269 (16.2)	94 (34.9)	175 (65.1)	
2	103 (6.2)	50 (48.5)	53 (51.5)	
3	84 (5.1)	42 (50.0)	42 (50.0)	
Fall concern (imputed)				
Low 16–19	755 (45.4)	174 (23.0)	581 (77.0)	<.001
Medium 20–27	547 (32.9)	143 (26.1)	404 (73.9)	
High >27	360 (21.7)	132 (36.7)	228 (63.3)	
CES-D				
Not depressed	1306 (79.3)	340 (26)	966 (74.0)	.04
Depressed	341 (20.7)	108 (31.7)	233 (68.3)	
Dementia screening				
Negative	1603 (96.9)	434 (27.1)	1169 (72.9)	1
Positive	52 (3.1)	14 (26.9)	38 (73.1)	
BMI				
Underweight <18.5	26 (1.6)	5 (19.2)	21 (80.8)	.65
Normal 18.5–24.9	462 (27.8)	121 (26.2)	341 (73.8)	
Overweight 25–29.9	710 (42.7)	190 (26.8)	520 (73.2)	
Obese ≥30	464 (27.9)	133 (28.7)	331 (71.3)	
SPPB score for chair stand				
0	59 (3.5)	19 (32.2)	40 (67.8)	.56
1	263 (15.8)	80 (30.4)	183 (69.6)	
2	422 (25.4)	110 (26.1)	312 (73.9)	
3	498 (30)	132 (26.5)	366 (73.5)	
4	420 (25.3)	108 (25.7)	312 (74.3)	
SPPB balance score (imputed)				
0–1	50 (3.0)†	17 (34.0)	33 (66.0)	.46
2	119 (7.2)	37 (31.1)	82 (68.9)	
3	119 (7.2)	30 (25.2)	89 (74.8)	
4	1374 (82.7)	365 (26.6)	1009 (73.4)	
SPPB gait speed score (imputed)				
0–1	36 (2.2)‡	13 (36.1)	23 (63.9)	.20
2	129 (7.8)	43 (33.3)	86 (66.7)	
3	395 (23.8)	106 (26.8)	289 (73.2)	
4	1102 (66.3)	287 (26.0)	815 (74.0)	
Number of chronic diseases				
Mean (SD)	1.9 (1.3)	2 (1.3)	1.8 (1.3)	.02

BMI, body mass index; CES-D, Center for Epidemiologic Studies Depression Scale; SD, standard deviation.
Numbers inside parentheses represent row percentages and are rounded to the nearest first decimal.
*Based on χ^2 test.
†n = 13 in the "0" category.
‡n = 4 in the "0" category.

Results

A total of 449 participants (27% of the total sample) reported at least 1 fall in the 12 months preceding the 2014 follow-up interview. χ^2 tests found no significant differences between incidence of falls across age groups (27.6% for age group of 64–69 years vs 26.2% for 70–75 years, *P* = .56). However, falls happened more frequently in women (29.6% in women vs 24.1% in men, *P* = .01). Past history of fall (before 2012) and FoF were significantly associated with the occurrence of falls in the year preceding 2014 data collection (*P* < .001 for both risk factors). Of only 20% (n = 100) of those who experienced a fall required medical care. The rate of hospitalization was much lower; only 16 individuals were hospitalized for treatment of fall-related injuries. Depression and number of chronic diseases (assessed at baseline in 2012) were significantly associated with subsequent falls (*P* = .04 and .02, respectively). Screening positive for dementia, obesity (body mass index ≥30), and physical performance as measured by the 3 SPPB components, were not significantly associated with subsequent falls in bivariate analyses (Table 1).

CHAID procedure identified 6 end nodes with 3 levels of partition and 4 partitioning variables. These variables (all assessed at the baseline) included "number of falls during the preceding year," "fear of falling," "SPPB chair stand score," and "age" (Figure 1). The first split in the tree involved "2 or more falls" vs "fewer than 2 falls" in the year preceding the 2012 baseline interview. Fifty percent of the respondents who fell at least 2 times in the year before the 2012 interview fell again during the 2 years of follow-up, whereas only 21% of the respondents who reported no falls in the year before 2012 had at least 1 fall during the year preceding 2104. CHAID further identified 2 end nodes for respondents who fell at least 2 times in the year before 2012 interview and 1 node for respondents who did not fall (Figure 1). Among the "2 or more falls" subgroup, those with very low scores (0 and 1) or high scores (3 and 4) for SPPB chair stands formed another end node (number 6, Figure 1). Of these, younger participants (65–69 years old) were more likely to fall (64% in 64- to 69-year-old age group vs 46.4% in 70- to 75-year-old age group).

To test the accuracy of the CHAID analysis, we performed a 10-fold crossvalidation by re-executing the model 10 times. The obtained misclassification error was 27.1%, which remained within 95% confidence interval (CI) of the sample misclassification error (23.6%–28.0%). With respect to specific risk for falls in subgroups of populations, CHAID models showed that those who had more than 2 falls during the year preceding the 2012 interview, their SPPB chair stand scores was 0, 1, 3, or 4, and were between 64 and 69 years old (node 9), had 5.3 times higher odds for a fall experience in 2014 (OR 5.25, 95% CI 3.16-8.88) compared with those participants who were not classified at this node. No history of falls in the year preceding the

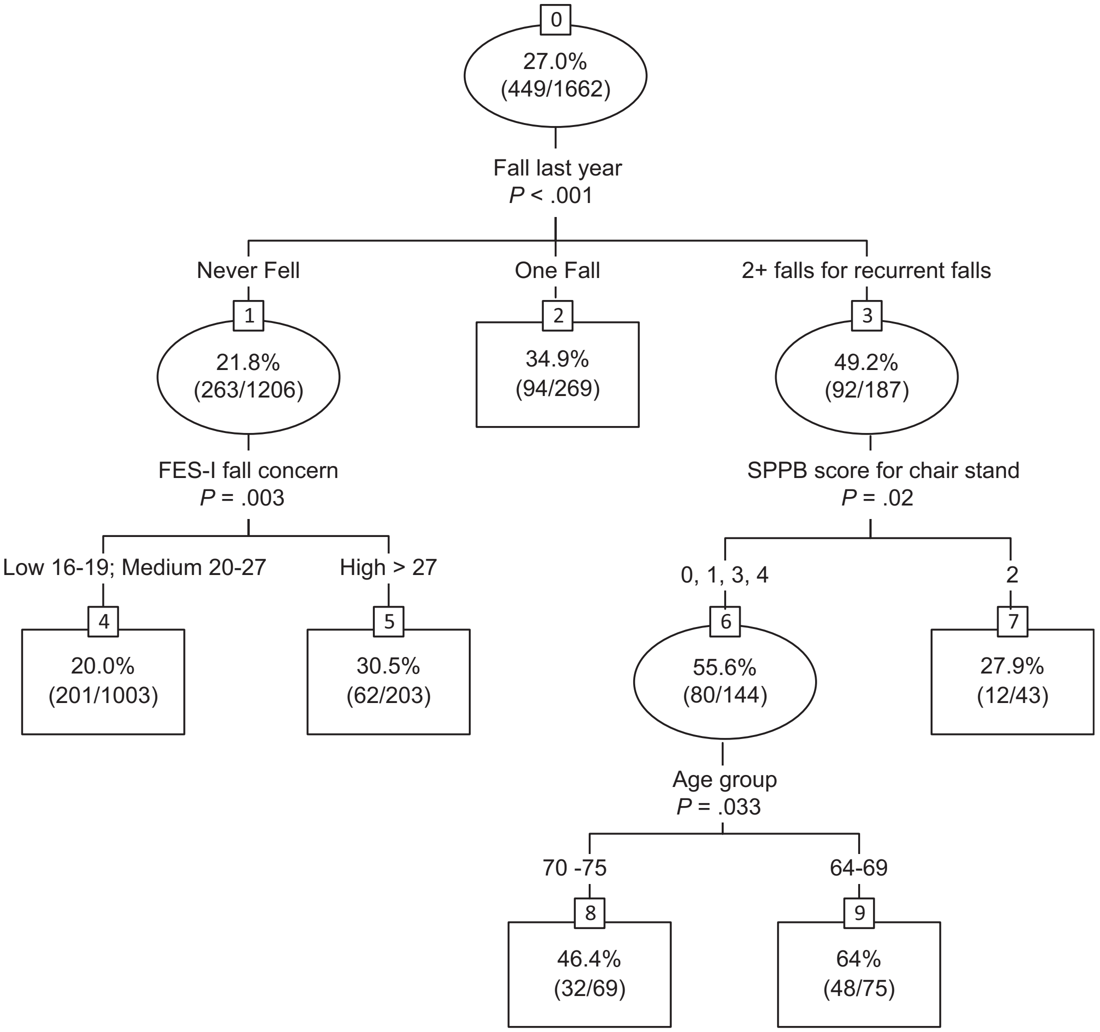

Fig. 1. Classification tree using the CHAID method for predicting the risk of falling in community-dwelling older persons at 2-year follow-up. Each divisible group is identified as an ellipse (nodes 0, 1, 3, and 6) and end nodes as a rectangle (2, 4, 5, 7, 8, and 9). Numbers inside nodes represent incidence rates (in percentage), number of fallers, and total number of participants who are indicated by the node.

2012 interview and low or medium fall concerns (node 4) showed a protective effect. Those classified at this node were 58% less likely of fall in 2014 (OR 0.42, 95% CI 0.33–0.52). Our multiple logistic regression models revealed that the number of falls in the year preceding the 2012 interview and FoF, both were independently associated with falls during the year before 2014 with the largest OR for the history of 3 falls (OR 3.06, 95% CI 1.92–4.90) (Figure 2).

CHAID correctly classified 1186 of 1213 nonfallers (specificity: 97.8%, NPV: 74.7%) and 48 of 449 fallers (sensitivity: 10.7%, PPV: 64.0%). Multiple logistic regression model showed a lower specificity (65.5%) by identifying 795 nonfallers (NPV: 65.5%) but higher sensitivity (56.8%) by identifying 255 fallers (PPV: 56.8%). The classification accuracies were 74.2% for CHAID and 63.2% for multiple logistic regression models.

Discussion

Regression tree analysis of risk for falling in this 2-year prospective cohort study resulted in a classification tree with 6 end groups. All end groups could be easily identified with 3 measurable predictors (number of previous falls, FoF, and time of chair rise). These indicators were able to identify those with more than 50% probability of falling.

Fall history in the year before the baseline interview (2012) was identified by the CHAID procedure as the first splitter variable in the model. Among the subgroup of older adults without a history of falls, those with a high concern of falling had the highest risk of falls. Within the subgroups of recurrent fallers (2 or more), both low and high scores for chair stand subscale of SPPB were associated with the highest risk of falling. Because the number of participants with injurious falls (falls requiring medical care) was low, it was not included as a separate variable in the models.

We identified FoF as the strongest predictor in those who had not fallen in the year preceding the baseline 2012 survey, thus, the primary predictor of the first fall. Traditionally high FoF (Falls Efficacy Scale-International-I score >27) is considered an important consequence of falling (although FoF can exist in older adults with no history of falls) as well as a risk factor for falls.[4] Other studies also identified FoF as a risk factor for falling using both logistic regression models[37,38] and regression tree analysis.[20] This relationship is being explained by 2 hypotheses. The first postulates that FoF leads to self-imposed restriction of activities, and this may cause a decline in physical capacity and, therefore, an increased risk of falling.[39] Other hypothesis emphasizes the role of FoF-related changes in gait that leads to unsafe gait and subsequently higher occurrence of falls.[20]

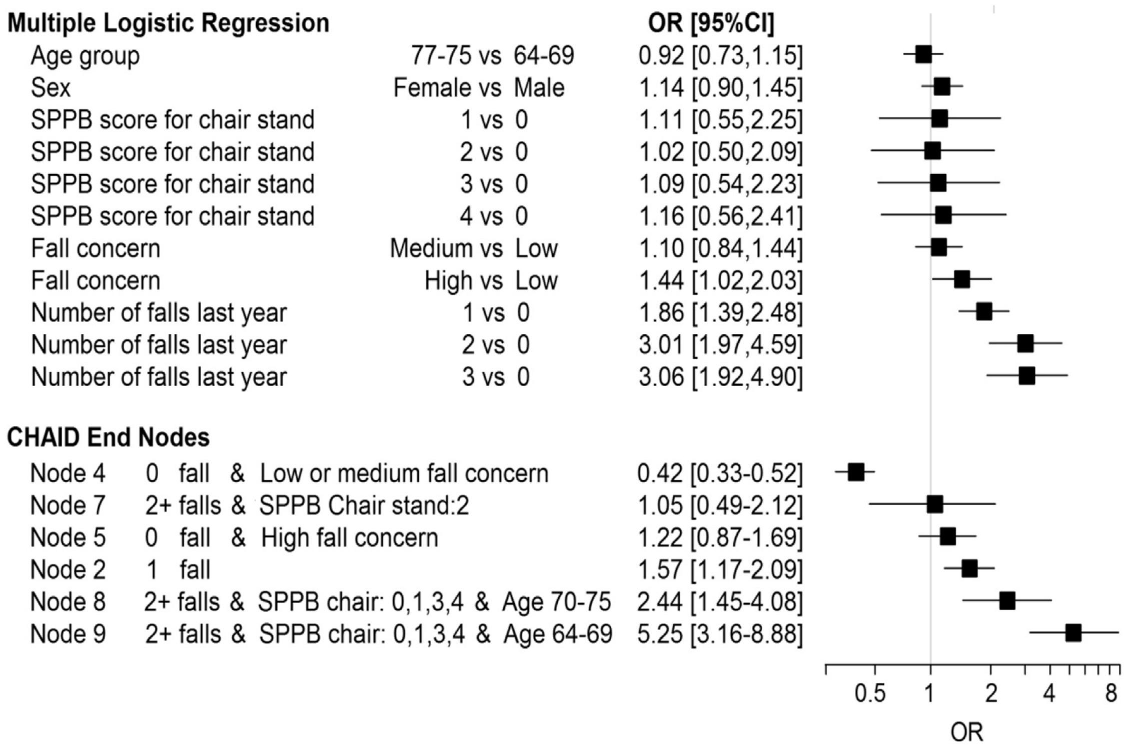

Fig. 2. ORs and 95% CIs for the incidence of falls according to single risk factors and combination of risk factors (n = 1662).

In the regression tree, fall history was the first splitter variable; this indicates that the importance of other identified risk factors such as FoF and functional limitations varies according to the status of fall history. This finding is particularly useful in designing targeted intervention programs for specific subgroups. For example, older people with no previous falls but with high concerns for falls should also be included in fall prevention programs.[40]

The time to complete chair stand tests has been previously reported as a predictor of falls.[5] Analysis of longitudinal studies either using logistic regression models[41] or through regression tree analysis[9,16] demonstrated that impaired mobility is a risk factor for falling. Low muscle strength and poor physical performance may enforce the impairment of postural reflexes and, therefore, increase the risk of falls during transfers or ambulation.[42] The counterintuitive finding that high scores for SPPB chair stands (less than 13.6 seconds) is a predictor for falls among the youngest age group (65–69 years old) has several explanations. Boulgarides et al[43] reported that older people with higher scores in Berg Balance Scale, which also contains a sit-to-stand task, fall more frequently. They argued that more active participants are more likely to engage in tasks that put them at a greater risk for falls. This reported ceiling effect can also be true for our study population, which includes healthy and active community-dwelling older adults.

In general, age is an established risk factor for falls in community-dwelling older adults[5]; however, several community-based longitudinal studies failed to identify age as an independent risk factor.[9,12,18] In our analysis, age did not add predictive power to the proposed solution. This finding may be related to the relatively young age of our study population. Interestingly, the increased risk of falling associated with older age appears to be due to the accumulation of other risk factors as people age, rather than intrinsic to aging itself.[44]

Primary care providers have an important role to identify patients with high risk of falling. However, the extent to which a multifactorial approach to assess modifiable risk factors is feasible to be incorporated in daily practice of primary care providers is limited.[45] Several guidelines for improving multifactorial risk of falling assessment in older adults in primary care practice have been proposed.[46] However, no single screening test is able to identify those in high risks of falling.[47] Our algorithm is evidence that can foster the use of specific assessment tools in the identification of subgroups of older adults at high risk of falls in primary care settings.

This study has several strengths. First relates to our use of the tree-based methodology that provides a number of advantages over logistic regression models. This methodology does not require any priori distributional assumption and information about the underlying relationships between variables. Furthermore, despite the fact that the findings of the tree-based analyses do not necessarily imply causal relationships, our results could also be useful to stratify risks and to determine prognosis of falling. Second, CHAID allows the construction of directly applicable fall risk profiles. We showed that by only a few measured predictors, primary care providers can identify those with high risk of falling. Third, we tested the robustness of our CHAID models by performing multiple logistic regression analyses and obtained similar results. The fourth strength related to the fact that we used population samples from different socioeconomic and cultural backgrounds; thus, the suggested algorithm could be implementable in different older adult populations. Finally, our simple algorithm is more feasible for use in primary care and permits quick identification of high-risk participants who can further undergo more complex assessments.

We also recognize the limitations of our study. First, our tree analyses were exploratory and in need of further tests in independent populations. However, our use of large cross-cultural samples provides some evidence on the universality of our findings. Second, one of the criticisms of classification and regression tree analyses is that because of sequential nature of the method and the inexactness of the corrections, variables with few distinct values (such as dichotomous variables) are more likely to get selected.[48] Although we cannot rule out the possibility of this methodological issue, we should note that variables with more than 2 categories such as FoF were also identified by our tree models. Third, because this classification tree was developed in a sample of community-dwelling older adults aged between 65 and 74 years, this algorithm might not be generalizable to people older than 75 years or frailer institutionalized seniors. Finally, because self-reported data were used for the assessment of falls, recall error is a possibility; however, because there is no reason to think "recall" is related to other factors included in this analysis, any associated misclassification most probably will be nondifferential.

Conclusions

CHAID identified specific combinations of risk factors for both recurrent falls and new falls in our international samples of older people aged between 65 and 74 years. The combination of risk factors most associated with recurrent falls was FoF and low score in chair stand tests, whereas the combination most associated with at least 1 fall only included high concerns of FoF. Thus, FoF emerged as the risk factor that is strongly associated with both new and recurrent falls. The simplicity of our approach and its high specificity imply its usefulness to detect older adults at high risks of falling in primary care settings.

References

1. Rubenstein LZ. Falls in older people: Epidemiology, risk factors and strategies for prevention. Age Ageing 2006;35:37–41.
2. Frith J, Davidson J. Falls. Rev Clin Gerontol 2013;23:101–117.
3. Voermans NC, Snijders AH, Schoon Y, Bloem BR. Why old people fall (and how to stop them). Pract Neurol 2007;7:158–171.
4. Masud T, Morris RO. Epidemiology of falls. Age Ageing 2001;30:3–7.
5. Ambrose AF, Geet P, Hausdorff JM. Risk factors for falls among older adults: A review of the literature. Maturitas 2013;75:51–61.
6. Inouye SK, Studenski S, Tinetti ME, Kuchel GA. Geriatric syndromes: Clinical, research, and policy implications of a core geriatric concept. J Am Geriatr Soc 2007;55:780–791.
7. Ganz DA, Bao Y, Shekelle PG, et al. Will my patient fall? JAMA 2007;297:77–86.
8. Tinetti ME, Kumar C. The patient who falls: "It's always a trade-off". JAMA 2010;303:258–266.
9. Stel VS, Pluijm SM, Deeg DJ, et al. A classification tree for predicting recurrent falling in community-dwelling older persons. J Am Geriatr Soc 2003;51:1356–1364.
10. Pluijm SM, Smit J, Tromp EA, et al. A risk profile for identifying community-dwelling elderly with a high risk of recurrent falling: Results of a 3-year prospective study. Osteoporosis Int 2006;17:417–425.
11. Shumway-Cook A, Silver IF, LeMier M, et al. Effectiveness of a community-based multifactorial intervention on falls and fall risk factors in community-living older adults: A randomized, controlled trial. J Gerontol A Biol Sci Med Sci 2007;62:1420–1427.
12. Leclerc BS, Bégin C, Cadieux É, et al. Risk factors for falling among community-dwelling seniors using home-care services: An extended hazards model with time-dependent covariates and multiple events. Chron Dis Can 2008;28:111–120.
13. Lemon SC, Roy J, Clark MA, et al. Classification and regression tree analysis in public health: Methodological review and comparison with logistic regression. Ann Behav Med 2003;26:172–181.
14. Malley J, Tutz G. An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. Psychol Methods 2009;14:323–348.
15. Kuhn L, Page K, Ward J, Worrall-Carter L. The process and utility of classification and regression tree methodology in nursing research. J Adv Nurs 2014;70:1276–1286.
16. Lamb SE, McCabe C, Becker C, et al. The optimal sequence and selection of screening test items to predict fall risk in older disabled women: The women's health and aging study. J Gerontol A Biol Sci Med Sci 2008;63:1082–1088.
17. Leclerc BS, Begin C, Cadieux E, et al. A classification and regression tree for predicting recurrent falling among community-dwelling seniors using home-care services. Can J Public Health 2009;100:263e7.
18. Delbaere K, Close JC, Heim J, et al. A multifactorial approach to understanding fall risk in older people. J Am Geriatr Soc 2010;58:1679–1685.
19. Yamashita T, Noe D, Bailer AJ. Risk factors of falls in community-dwelling older adults: Logistic regression tree analysis. The Gerontologist 2012;52:822–832.
20. Kabeshova A, Annweiler C, Fantino B, et al. A regression tree for identifying combinations of fall risk factors associated to recurrent falling: A cross-sectional elderly population-based study. Aging Clin Exp Res 2014;26:331–336.
21. Marschollek M, Gövercin M, Rust S, et al. Mining geriatric assessment data for in-patient fall prediction models and high-risk subgroups. BMC Med Inform Decis Mak 2012;12:19.
22. Zunzunegui MV, Alvarado BE, Guerra R, et al. The mobility gap between older men and women: The embodiment of gender. Arch Gerontol Geriatr 2015;61:140–148.
23. Sousa DA, Guerra RO, Tu MT, et al. Life course adversity and physical performance across countries among men and women aged 65-74. PLoS One 2014;9:1–10.
24. De Yébenes MJ, Otero A, Zunzunegui MV, et al. Validation of a short cognitive tool for the screening of dementia in elderly people with low educational level. Int J Geriatr Psychiatry 2003;18:925–936.
25. Lamb SE, Jørstad-Stein EC, Hauer K, et al. Prevention of Falls Network Europe and Outcomes Consensus Group. Development of a common outcome data set for fall injury prevention trials: The Prevention of Falls Network Europe consensus. J Am Geriatr Soc 2005;53:1618–1622.
26. Yardley L, Beyer N, Hauer K, et al. Development and initial validation of the Falls Efficacy Scale-International (FES-I). Age Ageing 2005;34:614–619.
27. Auais M, Alvarado BE, Curcio CL, et al. Fear of falling as a risk factor of mobility disability in older people at five diverse sites of the IMIAS study. Arch Gerontol Geriatr 2016;66:147–153.
28. Gutierrez P, Beland F, Del Ser T, Wolfson C. Development of simple cognitive function measures in a community dwelling population of elderly in Spain. Int J Geriatr Psychiatry 2000;5:130–140.
29. Radloff LS. The CES-D scale: A self-report depression scale for research in the general population. Appl Psychol Meas 1977;1:385–401.
30. Ylli A, Miszkurka M, Phillips S, et al. Clinically relevant depression in old age: An international study with populations from Canada, Latin America and Eastern Europe. Psychiatry Res 2016;241:236–241.
31. Guralnik JM, Ferrucci L, Simonsick EM, et al. Lower-extremity function in persons over the age of 70 years as a predictor of subsequent disability. N Engl J Med 1995;332:556–561.
32. Nagi SZ. An epidemiology of disability among adults in the United States. The Milbank Memorial Fund Q Health Soc 1976;54:439–467.
33. Freire AN, Guerra RO, Alvarado B, et al. Validity and reliability of the short physical performance battery in two diverse older adult populations in Quebec and Brazil. J Aging Health 2012;24:863–878.
34. Biggs D, de Ville B, Suen E. A method of choosing multiway partitions for classification and decision trees. J Appl Stat 1991;18:49–62.
35. Kass G. An exploratory technique for investigating large quantities of categorical data. Appl Stat 1980;29:119–127.
36. Goodman LA. Simple models for the analysis of association in cross-classifications having ordered categories. J Am Stat Assoc 1979;74:537–552.
37. Lajoie Y, Gallagher SP. Predicting falls within the elderly community: Comparison of postural sway, reaction time, the Berg balance scale and the Activities-specific Balance Confidence (ABC) scale for comparing fallers and non-fallers. Arch Gerontol Geriatr 2004;38:11–26.
38. Landers MR, Oscar S, Sasaoka J, Vaughn K. Balance confidence and fear of falling avoidance behaviour are most predictive of falling in older adults: Prospective analysis. Phys Ther 2016;96:433–442.
39. Filiatrault J, Belley A, Laforest S, et al. Fear of falling among seniors: A target to consider in occupational and physical therapy practice? Phys Occup Ther Geriatr 2013;31:197–213.
40. Gomez F, Curcio CL. The development of a fear of falling interdisciplinary intervention program. Clin Interv Aging 2007;2:661–667.
41. Moreland JD, Richardson JA, Goldsmith CH, Clase CM. Muscle weakness and falls in older adults: A systematic review and meta-analysis. J Am Geriatr Soc 2004;52:1121–1129.
42. Delbaere K, Van den Noortgate N, Bourgois J, et al. The Physical Performance Test as a predictor of frequent fallers: A prospective community-based cohort study. Clin Rehabil 2006;20:83–90.
43. Boulgarides LK, McGinty SM, Willett JA, Barnes CW. Use of clinical and impairment based tests to predict falls by community-dwelling older adults. Phys Ther 2003;83:328–339.
44. Grundstrom AC, Guse CE, Layde PM. Risk factors for falls and fall-related injuries in adults 85 years of age and older. Arch Gerontol Geriatr 2012;54:421–428.
45. Askari M, Eslami S, van Rijn M, et al. Assessment of the quality of fall detection and management in primary care in The Netherlands based on the ACOVE quality indicators. Osteoporos Int 2016;27:569–576.
46. Phelan EA, Aerts S, Dowler D, et al. Adoption of evidence-based fall prevention practices in primary care for older adults with a history of falls. Front Public Health 2016;4:190.
47. Lusardi MM, Fritz S, Middleton A, et al. Determining risk of falls in community dwelling older adults: A systematic review and meta-analysis using post-test probability. J Geriatr Phys Ther 2017;40:1–36.
48. Loh WY. Classification and regression trees. WIREs data mining and knowledge. Discovery 2011;1:14–23.