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Risk Factors of Falls in Community-Dwelling Older Adults: Logistic Regression Tree Analysis

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Purpose of the Study: A novel logistic regression tree-based method was applied to identify fall risk factors and possible interaction effects of those risk factors. ***Design and Methods:*** A nationally representative sample of American older adults aged 65 years and older (*N* = 9,592) in the Health and Retirement Study 2004 and 2006 modules was used. Logistic Tree with Unbiased Selection, a computer algorithm for tree-based modeling, recursively split the entire group in the data set into mutually exclusive subgroups and fit a logistic regression model in each subgroup to generate an easily interpreted tree diagram. ***Results:*** A subgroup of older adults with a fall history and either no activities of daily living (ADL) limitation and at least one instrumental activity of daily living or at least one ADL limitation was classified as at high risk of falling. Additionally, within each identified subgroup, the best predictor of falls varied over subgroups and was also evaluated. ***Implications:*** Application of tree-based methods may provide useful information for intervention program design and resource allocation planning targeting subpopulations of older adults at risk of falls.

Key Words: Fall risk factors, Logistic regression tree, Injury, Health and Retirement Study, LOTUS

Nearly 40% of older adults fall at least once a year (Kannus et al., 1999; Rubenstein, 2006). Falls may result in negative health consequences, such as limitations in everyday activities (e.g., fear of falls) and severe injuries including hip fracture, which leads individuals to be bedridden or even to death (Howland et al., 1998; Tinetti, Gordon, Sogolow, Lapin, & Bradley, 2006; World Health Organization, 2008; Zijlstra et al., 2007). Generally, falling is referred to as one of the geriatric syndromes because of its complex occurrence mechanisms resulting not only from one or more discrete diseases but also from accumulated effects of impairments in multiple systems (Flacker, 2003; Tinetti, Inouye, Gill, & Doucette, 1995; Tinetti, Williams, & Gill, 2000). As such, a fall prevention program requires developing intensive interventions (e.g., multifaceted intervention to address multiple fall risk factors; Filiatrault et al., 2007; Hornbrook et al., 1994; Rizzo et al., 1998; Rubenstein & Josephson, 2002).

Beyond the immediate impact of a fall for an individual, there are serious public health implications of a high incidence of falling among older adults. Falling is one of the most challenging and costly public health concerns in the United States (e.g., $19 billion in 2000 USD for fall-related medical care: Stevens, Corso, Finkelstein, & Miller, 2006). In addition, falling is likely to continue impacting the cost of the long-term care in accordance with ongoing population aging because the majority of falls occurs in older populations. Indeed, the population aged 65 years and older is expected to be 72 million by 2030 (Federal Interagency Forum on Aging-Related Statistics, 2010).

Previous studies report a number of fall risk factors in community-dwelling older adults. To begin, a set of demographic factors predict falls. For example, older age is associated with greater risk of falls, arguably because of chronic disease and age-related decline of physical/cognitive function (Biderman, Cwikel, Fried, & Galinsky, 2002; Jacobsen et al., 1990; Nevitt, Cummings, Kidd, & Black, 1989; Robbins et al., 1989; Rubenstein, 2006; Tideiksaar, 2002). Accordingly, other demographic/socioeconomic characteristics including gender, race, marital status, education, income, and health resources (e.g., health insurance) are also known to be fall risk factors because particular subgroups (i.e., women, White race, married couples, higher income group) are more likely to live longer and stay healthier than their counterparts (Baker, 1992; Oliver, 2007; Steinman, Pynoos, & Nguyen, 2009).

Also, medical conditions (e.g., cancer, diabetes, heart disease, arthritis) and their risk factors (e.g., high blood pressure, health behaviors such as smoking and drinking) are known to be associated with fall risk (Gardner, Buchner, Robertson, & Campbell, 2001; Kannus, Sieven, Palvanen, Javinen, & Parkkari, 2005; Leveille et al., 2002). Although specific etiological associations between the medical conditions and the fall risks are still unclear, stress and side effects from medical treatment, medication intake, and disease management behaviors (e.g., physical activity, dietary change) likely represent important risk factors for predicting higher risk of falls (Campbell, 1991; Schwartz et al., 2002). On one hand, medical conditions could be indicators of poor health status, which leads to greater risk of falls (Friedman, Munoz, West, Rubin, & Fried, 2002). On the other hand, existence of medical conditions could lead to lower rate of poor health behaviors like smoking and drinking, presumably because consciousness and fear of deteriorating conditions in older populations (Bogg & Roberts, 2004; Pleis, Ward, & Lucas, 2010). Additionally, greater numbers of functional impairments (e.g., limitations in activities of daily living [ADL] and instrumental activities of daily living [IADL]) and physical limitations (e.g., bending knees) generally increase fall risks because these limitations translate into additional burdens on regular everyday activities (Lord, Menz, & Tiedemann, 2003; O'Loughlin, Robitaille, Boivin, & Suissa, 1993; Tinetti, Speechley, & Ginter, 1988; Todd & Skelton, 2004; Wallace et al., 2002).

Finally, previous studies report that other fall risk factors including fall history and incontinence are associated with fall risks (Brown et al., 2000; Flacker, 2003; Pluijm et al., 2006). Environmental hazards also play an important role in the context of falls because some risk factors such as functional limitations are often influenced by individuals' living environments (Clemson, Mackenzie, Ballinger, Close, & Cumming, 2008; Stel et al., 2003; Zecevic, Salmoni, Lewko, Vandervoort, & Speechley, 2009). It must be noted that the concept of geriatric syndrome suggests the need to examine all risk factors and the relationships between them (i.e., interaction effects) in a fall study.

The health disparity research model advocates identifying individuals at higher risk as an indispensable first step to address falling as a highly prevalent public health problem (Kilbourne, Switzer, Hyman, Crowley-Matoka, & Fine, 2006). However, the American older population is demographically (e.g., race, ethnicity), socioeconomically (e.g., income, educational attainment), and physically (e.g., chronic illness, functional limitation) diverse (Administration on Aging, 2009). As such, neither a one-size-fits-all intervention program for the entire population (i.e., population approach) nor a tailored program for each individual older person (i.e., individual approach) is realistic (Rose, Khaw, & Marmot, 2008). The population-based program may not be viable due to heterogeneity of the population, whereas an individualized program may not be viable due to the tremendous expense of implementing a fully customized intervention (Friedman, Corwin, Dominick, & Rose, 2009; Filiatrault et al., 2007; Neyens et al., 2009; Rose et al., 2008; Shaw, Huebner, Armin, Orzech, & Vivian, 2009; Stel et al., 2003). In addition, some fall risk factors may be more or less relevant to certain subpopulations (e.g., ADL limitations for individuals with fall history vs. those without; age for men vs. women; Shumway-Cook et al., 2007). As a compromise to population-based or individualized fall prevention programs, developing risk prediction models separately for homogeneous subpopulations allows more efficient, flexible, and targeted intervention program designs. Generally, targeting the most vulnerable populations results in the greatest impact of intervention programs (Glasgow, Lichtenstein, & Marcus, 2003).

Building on the health disparity research model (Kilbourne et al., 2006) and the concept of geriatric syndrome (Flacker, 2003), this study employs a logistic regression tree-based method (Chan & Loh, 2004; Loh, 2007) to detect subpopulations at risk of falls according to the known fall risk factors and their interactions. Although previous studies using traditional methods (e.g., bivariate tests, binary logistic regression) to examine the impact of one fall risk factor at a time have significantly advanced the study of fall risk factors, systematic identification of at-risk subpopulations based on multiple risk factors is less common. Although regression tree-based methods have been used to identify high-risk subgroups for myocardial infarction, asthma, diabetes, prostate cancer, and falls in some large population-level studies (Garzotto et al., 2005; Herman, Smith, Thompson, Engelgau, & Aubert, 1995; Lemon, Roy, Clark, Friedmann, & Rakowski, 2003; Lieu, Quesenberry, Sorel, Mendoza, & Leong, 1998; Marshall, 2001; Stel et al., 2003; Tsien, Fraser, Long, & Kennedy, 1998), these methods have not been applied to investigating fall risk factors in community-dwelling American older adults.

Design and Methods

Data from the Health and Retirement Study (HRS), an ongoing nationally representative panel study, were used in this analysis. The HRS has been conducted every 2 years since 1992 with the initial samples of 12,652 respondents aged 50 years and older, including oversamples of non-Hispanic Blacks, Hispanics, and residents of Florida. The survey contains extensive information on respondents' demographic characteristics, socioeconomic status, and health behaviors/status. A more detailed description of the HRS has been published elsewhere (Juster & Suzman, 1995). The current study uses the 2004 and 2006 core wave data in addition to the HRS RAND data, which contains derived variables for the HRS data users (St. Clair et al., 2010). This study includes HRS respondents who were 65 years and older at the time of HRS interview in 2004. Respondents with missing values or no answer to the fall-related questions (e.g., Have you fallen down in the last 2 years?) for the HRS interview in 2006 (n = 26) and in 2004 (n = 43) were excluded from the analysis. The fall status variable in 2006 was used to classify fallers and nonfallers, and the fall status variable in 2004 was used to define the respondents' fall history. All other variables are based on the HRS interview in 2004. The final sample size was 9,592.

Often, the data from the respondents with cognitive impairments are excluded from the analysis because of possible concerns about their ability to understand questions and communicate their answers accurately (Steinman et al., 2009; Tinetti et al., 1988). However, this study retains possibly cognitively impaired respondents who are identified by a 6 or lower score on the telephone interview of cognitive status (TICS) because such a condition may be associated with the risk of falls. Therefore, a dichotomous variable indicating if a respondent is cognitively impaired was included in the analysis.

Measures: Outcome Variable

Any fall is considered a potentially serious event for older individuals (Luukinen et al., 2000; Sterling, O'Connor, & Bonadies, 2001). As such, frequency, type (e.g., injurious), and severity of falls were not separately modeled. We modeled the dichotomous response, falls, that indicates if the respondent reported any fall between 2004 and 2006 at the time of HRS interviews in 2006.

Measures: Predictor Variables

Fall history (i.e., prior falls) is a dichotomous variable indicating if the respondent reported any fall between 2002 and 2004 HRS interviews.

Demographic and Socioeconomic Characteristics

Age (years) indicates the respondent's chronological age in years at the time of 2004 HRS interview. Years of education, household income, and assets record the respondent's socioeconomic measures. A series of dichotomous variables are coded, including race (White [reference group], Black, others [Hispanics and Asians]), gender (*female* vs. *male*), marital status (*married* vs. *not married*), and insurance (*insured* vs. *not insured*).

Health Status

Self-rated health is an ordinal variable recording 5 (*excellent*), 4 (*very good*), 3 (*good*), 2 (*fair*), and 1 (*poor*). The chronic illness dichotomous indicator variables are high blood pressure, diabetes, cancer, lung disease, heart disease, stroke, and arthritis. Prescription drug (vs. *no prescription drug*) indicates if the respondent regularly takes at least one prescription drug. Respondent's body mass index (BMI) was also included as a predictor variable. Although the statistical method in this study allows split point search for continuous measures only at the preselected percentile points, examining these percentiles is a sensible approach in the context of subgroup analysis. This may be particularly true for BMI because commonly used cut points (e.g., BMI greater than 30 indicates obesity) may not be applicable for subpopulations of older adults (e.g., Nishiwaki, Michikawa, Eto, & Takebayashi, 2011).

Functional Limitations

Self-rated vision is an ordinal variable recording 5 (*excellent*), 4 (*very good*), 3 (*good*), 2 (*fair*), and 1 (*poor*). ADL5 indicates the number of ADL, including bathing, dressing, eating, getting out of bed, and walking across a room, with which a respondent has limitations. IADL5 indicates the number of IADL, including making a phone call, managing money, taking medications, shopping for groceries, and preparing meals, with which the respondent has limitations. A series of dichotomous variables indicating incontinence, back problem, difficulty with kneeling, difficulty with extending arms above the shoulders, and cognitive impairment (the TICS score fewer than 7) are coded. The TICS is developed based on the Mini-Mental State Examination, which is a widely used simple assessment tool of cognitive functions (e.g., orientation of time and place, word recall; Brandt, Spencer, & Folstein, 1988; Folstein, Folstein, & McHugh, 1975). In the HRS modules, the modified TICS is used, and therefore, the scoring system is different from the original version (Ofstedal, Fisher, & Herzog, 2005).

Lifestyle

Smoker and drinker are dichotomous variables indicating if a respondent reported current smoking and drinking alcoholic beverages, respectively. The HRS classifies types of activities into vigorous (e.g., *running*, *swimming*, *gym workout*, *tennis*), moderate (e.g., *gardening*, *walking at a moderate pace*, *dancing*), and light (e.g., *vacuuming*, *laundry*, *home repairs*) activities. Three separate activity-related measures including light activity, moderate activity, and vigorous activity recorded the frequency of participation in each type of activity (5 [*every day*], 4 [*more than once a week*], 3 [*once a week*], 2 [*1–3 times a month*], and 1 [*never*]).

Statistical Methods

Summary statistics for the predictor variables are calculated separately for fallers and nonfallers. The Logistic Tree with Unbiased Selection (LOTUS) algorithm or logistic regression tree method is used to identify at-risk groups and fit a best simple logistic regression (i.e., logistic regression with a single predictor variable) for each subgroup defined as nodes in the tree (Chan & Loh, 2004; Hosmer & Lemeshow, 2004). LOTUS is a computer algorithm executing logistic regression tree analysis (available for download at http://www.stat.nus.edu.sg/~kinyee/lotus.html; October 19, 2011, date last accessed).

LOTUS can be considered a hybrid between two other general techniques used to model a two-level response variable: binary logistic regression and tree-based classification (e.g., Kolyshkina, Steinberg, & Cardell, 2003). In a logistic regression, the log odds of a fall is considered as a linear function of a set of predictor variables. Although examining interaction effects in a logistic regression model is possible, it is often a difficult task because these interactions must be prespecified based on previous studies and existing theories. Identifying relevant interactions can be particularly challenging when focusing on understudied populations and/or evaluating complex interactions (e.g., four-way interactions) due to lack of theory. To date, in the context of fall risk factors, complex interaction effects have not been explicitly studied.

On the other hand, tree-based classification methods, such as classification and regression trees, or CART (Breiman, Friedman, Olshen, & Stone, 1984), and the CHi-squared Automatic Interaction Detector, or CHAID (Kass, 1980), can be used to detect possible interactions between predictor variables automatically. These methods recursively partition a data set based on values of the predictor (i.e., splitter) variables to generate subgroups that are as homogeneous as possible in the response variable (i.e., fallers vs. nonfallers in this study). Tree models are valued for their ease of interpretability and automatic interaction detection, but they often lack the predictive power of logistic regression models.

LOTUS merges the desirable characteristics of these two methods. The recursive partitioning procedure in LOTUS is modified from commonly used tree-based classification methods (e.g., CART) in a manner that optimizes the performance of logistic regression models fit to each subgroup (Loh, 2006). Hence, LOTUS retains the automatic interaction detection and ease of interpretability of tree-based classifiers while building on the potential predictive power of logistic regression.

The LOTUS algorithm can be divided into two major interrelated processes: recursively splitting the data into subgroups (nodes) starting from all respondents in the data set (root node) and fitting a simple logistic regression model at each node. The process of selecting a simple logistic regression model for a node is embedded within the process of splitting a node, so we describe it first. Because a simple logistic regression model contains only one predictor variable, the variable selection method is quite straightforward: LOTUS chooses the predictor variable from the collection of numeric predictor variables that results in the model with minimum logistic deviance. This predictor variable and associated logistic regression are only used if this node ends up being a terminal node in the final tree.

In addition to fitting the logistic regression at each node, the algorithm examines candidate's splits for the node. These splits can be based on either numeric or categorical predictors. The process of splitting a node into two subgroups (child nodes) is more complex and proceeds as follows. First, the algorithm selects a predictor variable on which to split the data. The splitter chosen should exhibit the strongest evidence of a relationship (i.e., the smallest p value) among all the predictor variables with the outcome variable. To ensure a fair comparison between continuous and categorical variables, each continuous variable is temporarily divided into five groups at the sample quintile points, and a 2×5 contingency table is created with the outcome variable as rows and the five groups as columns. LOTUS then performs a chi-square–based test of independence for each predictor variable with the outcome variable and designates the predictor variable with the smallest significance probability (i.e., p value) as the splitter.

Finally, after the splitting variable is selected, a value at which to make the split is determined. The possible splits for ordinal or categorical predictor variables are determined by their defined levels. For a continuous variable, LOTUS examines a predetermined set of sample percentiles (30th, 40th, 50th, 60th, and 70th) as potential splitting values. LOTUS selects the splitting value to minimize the sum of the logistic deviance statistics of the resulting child nodes.

LOTUS applies these steps recursively beginning with a tree with no split and ending with a very complex tree that cannot be split further (i.e., terminal nodes cannot be split due to too few cases) and applies a 10-fold cross-validation process (see Breiman et al., 1984) to select the intermediate tree of optimal size as the final solution. In this cross-validation process, the data are first split into 10 subgroups where each observation is a member of only one subgroup. Trees of varying sizes (e.g., number of splits) are grown based on a data set defined by leaving out a particular subgroup. Predictions from each tree are applied to data in the omitted subgroup. This process is repeated 10 times—each time omitting a different subgroup. At the end of the 10 steps, LOTUS computes the mean logistic deviance statistic, a measure of the quality of fit, which is averaged over the 10 trees that were developed at each size. The tree size resulting in the smallest mean logistic deviance statistic is selected to produce the final tree. Based on the 0–*SE* criterion of Breiman et al., the original tree is pruned to the size that minimizes the mean deviance. In other words, the 0–*SE* criterion was used as the a priori stopping rule for the tree-based model building in this study.

Results

Table 1 shows the characteristics of the HRS respondents, including the means and standard deviations for continuous variables, percentages for categorical variables, 95% confidence intervals for differences in either means or proportions, and bivariate test results (t tests for continuous variables and chi-square tests for categorical variables). Approximately one third of the respondents report at least one fall between their 2004 and 2006 interviews. Fallers and nonfallers show different characteristics. A review of the marginal comparisons of the various predictor variables suggests that fallers are more likely to be older, women, less wealthy, unmarried, unemployed, and possess a history of falls. Also, the prevalence of chronic illnesses is higher in the fallers than nonfallers. More fallers report functional limitations, such as difficulties in ADLs, incontinence, back problems, difficulty with kneeling, and difficulty with extending arms. Finally, the fallers are less likely to engage in physical activities than the nonfallers.

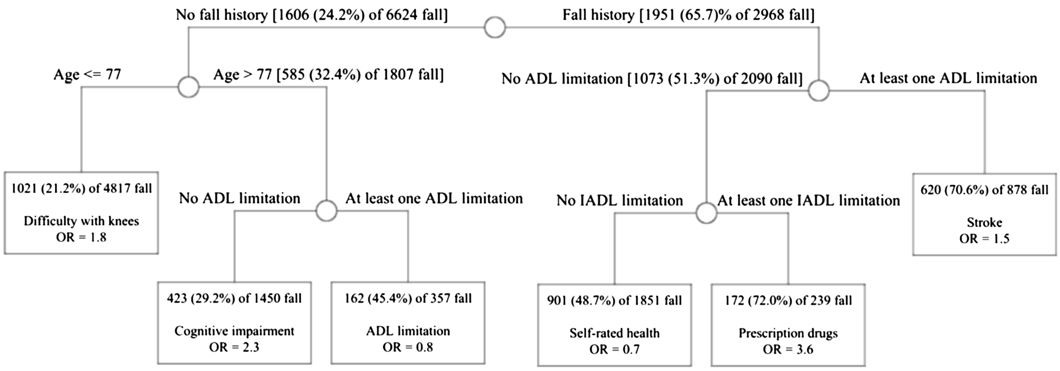
The logistic regression tree begins with all respondents in the root node (see Figure 1). The first split is determined by fall history. For those without fall history, the subgroup aged 78 years and older with at least one ADL limitation was at the highest risk of falls (45%). However, for those with fall history, the subgroups with at least one ADL limitation (71%) or no ADL limitation and at least one IADL limitation (72%) had the highest risks of falls. Overall, the subgroups of respondents without prior falls exhibited lower risks of new falls compared with those with prior falls. The subgroup at the lowest risk of falls included respondents aged 77 years or younger with no fall history (21%).

Table 1. Summary Statistics for HRS Respondents Stratified by Fall Status

	M (SD) or percentage			
	Total[a]	Nonfallers (N = 6,293)	Fallers (N = 3,299)	t or x^2 value (p)
Dependent variable				
Fall	34.3%	—	—	
Fall history				
Fall history	31.0%	20.3%	51.6%	984.2 (<.001)
Demographic and socioeconomic factors				
Age	74.2 (7.16)	73.4 (6.75)	75.8 (7.63)	−16.1 (<.001)
Female	57.8%	55.9%	61.4%	26.5 (<.001)
Blacks	13.0%	13.6%	11.8%	6.1 (.013)
Others	3.1%	3.2%	2.8%	0.9 (.351)
Married	58.5%	61.9%	53.4%	53.5 (<.001)
Education	11.9 (3.35)	12.0 (3.30)	11.7 (3.42)	4.1 (<.001)
Income ($USD)	45,543 (75,340)	48,028 (81,507)	40,801 (61,631)	4.5 (<.001)
Assets ($USD)	435,414 (1,355,916)	467,796 (1,562,194)	373,643 (827,555)	3.2 (<.001)
Employed	19.3%	21.6%	14.8%	63.0 (<.001)
Insured	61.4%	61.8%	60.7%	1.1 (.289)
Health status				
Self-rated health	2.90 (1.08)	3.19 (1.06)	2.81 (1.09)	270.7 (<.001)
High blood pressure	60.9%	59.3%	64.0%	19.9 (<.001)
Diabetes	19.9%	17.8%	23.9%	50.5 (<.001)
Cancer	16.6%	16.2%	17.4%	2.2 (.136)
Lung disease	10.6%	9.4%	12.8%	26.9 (<.001)
Heart disease	30.3%	27.0%	36.5%	93.4 (<.001)
Stroke	8.0%	6.1%	11.5%	83.4 (<.001)
Arthritis	67.7%	64.1%	74.4%	103.5 (<.001)
Prescription drug	86.7%	84.7%	90.6%	65.8 (<.001)
Body mass index (BMI)	26.88 (5.19)	26.9 (5.01)	27.2 (5.69)	−2.3 (.021)
Functional limitations factors				
Self-rated vision	3.2 (0.99)	3.26 (0.97)	3.07 (1.03)	91.8 (<.001)
Incontinence	23.2%	19.0%	31.3%	181.7 (<.001)
Back problem	35.7%	32.0%	42.8%	109.6 (<.001)
Cognitive impairment	12.6%	15.8%	10.9%	46.2 (<.001)
ADL limitations	0.35 (0.95)	0.24 (0.79)	0.58 (1.16)	384.6 (<.001)
Bathing	8.2%	5.5%	13.5%	182.1 (<.001)
Dressing	10.1%	7.2%	15.7%	174.5 (<.001)
Eating	3.8%	2.7%	5.9%	58.1 (<.001)
Getting out of bed	5.9%	3.9%	9.9%	139.1 (<.001)
Walking across a room	7.6%	4.8%	13.0%	205.1 (<.001)
Toileting	6.1%	4.3%	9.7%	106.9 (<.001)
IADL limitations	0.34 (0.95)	0.23 (0.79)	0.56 (1.18)	349.0 (<.001)
Phone	6.2%	4.5%	9.5%	91.2 (<.001)
Money	11.5%	8.8%	16.8%	136.2 (<.001)
Medications	4.2%	2.7%	7.1%	100.5 (<.001)
Shopping	14.7%	10.9%	22.1%	213.0 (<.001)
Preparing meals	14.2%	11.2%	19.9%	134.4 (<.001)
Using a map	27.9%	24.3%	34.8%	119.4 (<.001)
Difficulty with knees	49.7%	43.5%	61.8%	280.8 (<.001)
Difficulty with arms	17.4%	14.2%	23.4%	127.0 (<.001)
Lifestyle				
Smoker	9.2%	9.7%	8.3%	5.0 (.025)
Drinker	28.7%	30.7%	24.7%	38.6 (<.001)
Vigorous activity	1.82 (1.26)	1.93 (1.31)	1.67 (1.18)	82.1 (<.001)
Moderate activity	2.96 (1.33)	3.11 (1.27)	2.73 (1.39)	207.0 (<.001)
Light activity	3.24 (1.12)	3.36 (1.05)	3.09 (1.21)	150.0 (<.001)

Notes: Data source: Health and Retirement Study (HRS) 2004 and 2006 waves. ADL = activities of daily living; IADL = instrumental activity of daily living.

[a]All summaries based on N = 9,592 respondents.



1. Total sample size (i.e., root node) = 9,592
2. OR = odds ratio.
3. Greater score of self-rated health indicates more positive health.
4. Area Under the Receiver Operating Characteristics Curve (AUC) = 0.71

Figure 1. Logistic regression tree diagram.

LOTUS fits a simple logistic regression in each terminal node to identify the best predictor of falls within each subgroup. In the highest risk group (Figure 1), the individuals taking prescription drugs had 3.6 times the odds of falling as those who do not. Also, in the second highest risk group, the individuals who had stroke had 1.5 times the odds of falling as those who did not. In addition, the impact of cognitive impairment in the group identified by no fall history, aged 77 years and older, and no ADL limitation is worth noting although this group had relatively low risk of falls. In this group, individuals with cognitive impairment had 2.3 times the odds of falling as those without. As can be seen in Figure 1, a different variable was identified as the best predictor of falls within each subgroup.

The size of identified subgroups is an important point to consider, given possible practical applications. The previous studies adopted minimum subgroup sizes between 1% and 10% of the total sample, although such a decision should depend on focused outcome measures and available resources (Gruenewald, Mroczek, Ryff, & Singer, 2008; Lemon et al., 2003). In this study, the smallest subgroup identified according to our a priori stopping rule (i.e., the 0–*SE* rule) had 239 individuals (2.5% of total sample). As can be seen, the size of subgroups meets the suggestion made in previous studies. In fact, the smallest subgroup identified in our analysis had the highest risk of falls (72%), which warrants greater attention in practice. In terms of the overall quality of the model, the area under the receiver operating characteristics curve is 0.71. According to the criterion suggested by Swets (1988), the model has moderate accuracy.

Discussion and Implications

Building upon the public health disparities research model and the concept of geriatric syndrome, this study identifies subpopulations of community-dwelling older adults at risk of falls using a logistic regression tree method. The subgroups of older adults with fall histories, no ADL limitations, and at least one IADL limitation or with fall histories and at least one ADL limitation were at the highest risk of falls. Notably, fall history was chosen as the first splitter variable in the model. Overall, the identified subgroups of older adults according to fall history, age, and ADL/IADL limitations provide useful information not only for understanding the complex associations between risk factors but also for developing subgroup-level intervention programs. This capability of LOTUS also suggests great potential for application in other specific older populations (e.g., community members, hospital patients).

With regard to all the identified subgroups, fall history was the first splitter variable. That is, the importance of identified risk factors including age and ADL/IADL limitations varied according to the existence of fall history. This finding is particularly useful for designing intervention programs to achieve different goals. For instance, on one hand, an intervention program may consider primary prevention (i.e., improving fall risk factors to prevent first fall) targeting individuals aged 77 years and older when they have no fall history. On the other hand, an intervention program may focus on secondary/tertiary preventions (i.e., preventing recurrent falls) regardless of their age. As previous studies show, prevention of recurrent falls requires a different approach than the first fall, and therefore, the findings about fall history in this study reinforce the importance of previous falls (Deandrea et al., 2010).

As observed in most previous studies (Pluijm et al., 2006; Rubenstein, 2006; Steinman et al., 2009), older age was associated with a higher risk of falls. Older age can be thought of as a surrogate measure reflecting age-related physical functional decline and a number of chronic conditions, which are associated with fall risk (Lord, Sherrington, & Menz, 2007; Rubenstein, 2006). Given the geriatric syndrome, older age may be a summary marker of multiple conditions. However, the tree diagram in this study suggests that cut-offs near age 77 may be important for identifying higher and lower risk groups.

Generally, detecting complex interactions among the variables is challenging in traditional methods, such as linear regression and logistic regression (Noe, Nelson, Mehdizadeh, & Bailer, 2009); yet, the LOTUS algorithm identifies possible complex interactions between effects of fall history, older age, ADL limitations, and IADL limitations. Although the identified risk factors are generally associated with older age, insights about differences in the impact of each risk factor among subgroups (e.g., 77 years and younger vs. older) could inform the design of tailored intervention programs. Additionally, even within identified subgroups, the best predictor (e.g., prescription drugs, cognitive impairment, difficulty with knees) of falls varied. These risk factors that have been reported in other studies were also relevant to the specific subgroups identified in this study (Härlein, Dassen, Halfens, & Heinze, 2009; Hartikainen, Lönnroos, & Louhivuori, 2007). The insights regarding possible complex interactions are useful particularly in community settings because each community has an older population with distinct characteristics (e.g., demographic, socioeconomic, and health status). At the same time, it must be noted that possible interaction effects identified by the LOTUS algorithm do not necessarily suggest theoretical grouping. As such, validation studies using future surveys of the same or other populations are necessary.

Functional limitations as characterized by ADL and IADL limitations were significantly associated with the risk of falls (Kannus et al., 2005; Mann, 2005; O'Loughlin et al., 1993). Often, it is challenging to determine target groups for an intervention based on ADL/IADL limitations while simultaneously considering other risk factors due to their complex associations. In this study, whether the older adults had fall histories or not, the roles of ADL/IADL limitations were consistently associated with higher risks of falls. Additionally, ADL and IADL limitations were not important for the prediction of falls in the respondents aged 77 years and younger. As can be seen, depending on fall history and age, the impact of ADL and IADL limitations on the risk of falls differs.

One of the most significant contributions of this paper is to apply the logistic regression tree-based method (LOTUS) for a fall study. LOTUS has a number of benefits over traditional methods such as logistic regression, including applicability for a variety of data (e.g., health-related surveillance data), identifying at-risk groups that share the same characteristics (specific combinations of risk factors), and generating an easily interpretable tree diagram (Chan & Loh, 2004) that illustrates differing impacts of predictor variables on the risk of falls across subgroups. In addition, some hypotheses can be generated from analysis using tree-based methods. For instance, in this study, because the selected split variables are mostly related to fall history and functional statuses, other demographic and socioeconomic measures may not be directly associated with fall risks but instead indirectly related through functional statuses. Such findings are informative to design effective fall prevention programs targeting sets of high-risk subpopulations to maximize the impacts of interventions (Frohlich & Potvin, 2008; Glasgow et al., 2003). A tree-based method has potential to further advance fall studies from a public health standpoint (Lemon et al., 2003). Moreover, identifying subgroups at risk of falls provides useful information for policy planning (e.g., resource allocation).

However, there are several limitations in this study. Potentially important fall risk factors were not available in the HRS data. For instance, variables regarding living environments (Lord, Menz, & Sherrington, 2006; Stevens, Teh, & Haileyesus, 2010; Tinetti et al., 1988) and a number of physiological measures, such as muscular strength, reaction time, peripheral sensation, and others (Latt, Lord, Morris, & Fung, 2009; Lord et al., 2003) were not available. Therefore, future HRS modules may consider collecting additional information related to fall risk to replicate our study with additional potentially important variables. In addition, as with any statistical model, the performance of LOTUS depends on the agreement of the data with its internal assumptions. As such, there may be cases in which other standard methods outperform

LOTUS. Also, LOTUS currently does not allow taking survey weights into account. Additionally, split point search of continuous measures is limited to specific percentiles in LOTUS. From a methodological standpoint, these are desirable capabilities to be added in future development in LOTUS and other logistic regression tree algorithms. Finally, detailed classifications of falls (e.g., recurrent falls, injurious/noninjurious falls, injury severity, number of falls, season/time of falls, indoor/outdoor falls) were not examined due to the specific objectives of this study and the availability of information in the HRS data. The findings of this study need to be treated with proper perspective because each type of fall may have different risk factors and occurrence mechanisms (Pluijm et al., 2006; Stel et al., 2003).

In conclusion, this study identifies subpopulations of older adults with higher risks of falling and demonstrates the potential and usefulness of a logistic regression tree algorithm in a fall study. The subgroups of community-dwelling older adults with fall history, no ADL limitation, and at least one IADL limitation or those with at least one ADL limitation were at the highest risks of falls among all identified subgroups. Furthermore, prescription drug use and stroke status were important predictors within these two subgroups, respectively. These findings suggest that certain factors may be more or less relevant to the fall risk in each subgroup. In view of geriatric syndrome, each intervention program should be designed based on multiple sets of identified fall risk factors to prevent falls in specific target subgroups with consideration to their characteristics (e.g., demographic and socioeconomic status). Finally, methods like LOTUS could be useful in developing intervention programs targeting specific subpopulations as an alternative to the common population approach (e.g., one-size-fits-all) and individual approach (e.g., one-on-one).

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