


Comparison of Simple Versus Performance-Based Fall Prediction Models: Data From the National Health and Aging Trends Study

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Abstract

Objective: To compare the predictive ability of standard falls prediction models based on physical performance assessments with more parsimonious prediction models based on self-reported data. **Design:** We developed a series of fall prediction models progressing in complexity and compared area under the receiver operating characteristic curve (AUC) across models. **Setting:** National Health and Aging Trends Study (NHATS), which surveyed a nationally representative sample of Medicare enrollees (age ≥ 65) at baseline (Round 1: 2011-2012) and 1-year follow-up (Round 2: 2012-2013). **Participants:** In all, 6,056 community-dwelling individuals participated in Rounds 1 and 2 of NHATS. **Measurements:** Primary outcomes were 1-year incidence of “any fall” and “recurrent falls.” Prediction models were compared and validated in development and validation sets, respectively. **Results:** A prediction model that included demographic information, self-reported problems with balance and coordination, and previous fall history was the most parsimonious model that optimized AUC for both any fall (AUC = 0.69, 95% confidence interval [CI] = [0.67, 0.71]) and recurrent falls (AUC = 0.77, 95% CI = [0.74, 0.79]) in the development set. Physical performance testing provided a marginal additional predictive value. **Conclusion:** A simple clinical prediction model that does not include physical performance testing could facilitate routine, widespread falls risk screening in the ambulatory care setting.

Keywords

falls, fall risk, recurrent falls

Introduction

Falls are a common cause of morbidity and mortality in the elderly, leading to functional impairment and poor long-term outcomes. These outcomes include serious injury such as hip fractures, hospital re-admissions, increased mortality, and decreased quality of life (Ayoung-Chee et al., 2014; Brauer, Coca-Perrillon, Cutler, & Rosen, 2009; Dunn, Rudberg, Furner, & Cassel, 1992; Hartholt et al., 2011; Legters, 2002; Tinetti, 2003). The socioeconomic burdens of falls on the health care system are immense, with estimates of the annual cost of falls in the United States equaling US\$30 billion annually (Hartholt et al., 2011; Hendrie, Hall, Arena, & Legge, 2004; Stevens, Corso, Finkelstein, & Miller, 2006).

Numerous models have been developed to assess fall risk, typically relying on performance-based assessments of balance and strength (Covinsky et al., 2001; Guralnik et al., 1994; Lord, Menz, & Tiedemann, 2003; Pluijm et al., 2006; Russell et al., 2009; Stalenhoef, Diederiks, Knottnerus, Kester, & Crebolder, 2002). Although these assessments may provide valuable clinical data that

predict the mechanism of a fall or identify targets for intervention, they may be time-consuming and challenging to administer in the primary care setting, precisely where fall-risk assessments are critical to make (Johnson et al., 2008). For instance, well-validated assessment tools such as the Berg Balance Scale (BBS; Berg, 2009; Berg, Wood-Dauphinee, Williams, & Maki, 1992; Godi et al., 2013; Major, Fatone, & Roth, 2013) and the Short Physical Performance Battery (SPPB; Freire, Guerra, Alvarado, Guralnik, & Zunzunegui, 2012; Gómez,

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Curcio, Alvarado, Zunzunegui, & Guralnik, 2013; Guralnik et al., 1994; Vasunilashorn et al., 2009) have been shown to validly predict prospective fall risk in older individuals. However, these instruments consist of a number of physical assessment tasks (14 for BBS, 5 for SPPB) which may be difficult to administer in routine clinical practice given time, space, and personnel limitations.

A further limitation of current falls prediction models is that many have been developed using data from individual populations in specific clinical contexts such as the Emergency Department (Lord et al., 2003; Peeters, van Schoor, & Lips, 2009; Russell et al., 2009; Stalenoef, Diederiks, Knottnerus, de Witte, & Crebolder, 2000; Stalenoef et al., 2002). As such, the external validity of these prediction models is limited, and the applicability of these models to a general community-dwelling population is unclear (Peeters et al., 2009). Moreover, most validated models were developed to specifically address recurrent falls (≥ 2 per year), and fewer risk prediction models exist for overall falls (Lord et al., 2003; Stalenoef et al., 2000; Stalenoef et al., 2002).

In this study, we use data from the National Health and Aging Trends Study (NHATS) to compare simple versus more complex clinical prediction models for *all falls* and *recurrent falls* in community-dwelling older individuals. NHATS is a longitudinal, nationally representative study of the health, social, and environmental conditions of older individuals in the United States. We developed a series of falls prediction models based on these nationally representative data, and compared the predictive power of models with and without performance-based assessment. The goal of this study was to identify a falls prediction model that optimized efficiency, enhanced clinical ease of use, and carried external validity.

Method

NHATS Study Design

NHATS is a longitudinal study of Medicare enrollees (age ≥ 65) in the United States. During Round 1 of NHATS beginning in 2011, 12,411 individuals were selected and 8,245 completed interviews. The unweighted and weighted response rates were 70.9% and 71.3%, respectively. Of these 8,245 participants, 7,609 were community-dwelling and were administered the Sample Person (SP) questionnaire during a face-to-face interview and were considered in these analyses. Follow-up Round 2 interviews with the same individuals were conducted 1 year later beginning in 2012 with unweighted and weighted response rates of 86.1% and 85.3%, respectively (Kasper & Freedman, 2014). From the community-dwelling Round 1 population, participants who were alive at Round 2 were administered an identical SP questionnaire regardless of interval changes

in residential status ($N = 6,056$). Details of study design and instrumentation are available elsewhere (Kasper & Freedman, 2014; Montaquila, Freedman, Spillman, & Kasper, 2012; Montaquila, Freedman, Vicki, Spillman, & Kasper, 2014).

Risk Factors and Physical Assessment

Baseline data on sociodemographic characteristics and medical conditions were collected from Round 1 interviews. We selected variables that have a strong and consistent association with falls in the literature (Deandrea et al., 2010). Medical conditions included in prediction models were history of myocardial infarction, coronary artery disease, stroke, osteoporosis, diabetes mellitus, hypertension, vision impairment, and hearing impairment. We also considered self-perceived problem with balance and coordination assessed based on the following question: "In the last month, did you have problems with balance and coordination." Participants who reported having sustained at least one fall at the time of Round 1 interview were categorized as having a history of falls.

Trained NHATS study examiners administered the SPPB, which includes a series of standing balance tests, chair stands, and a 3-m walk (Freire et al., 2012). The standing balance tests involved three stances with graduated difficulty. The stances progressed from feet side-by-side, to semi-tandem position, to full-tandem position. Participants were asked to hold each stance for 10 s. Participants had to pass each balance stance successfully before moving to the next stance. Participants received a score of "not attempted" and were excluded from testing if either they or the examiner felt that the test was unsafe. If any balance stance was either not attempted or not completed successfully, no further balance stance was administered. Overall balance testing was scored from 0 to 4, with 0 indicating that none of the stances were attempted, 1 indicating completion of side-by-side testing, 2 indicating completion of semi-tandem testing and either not attempting or holding full-tandem stance for < 3 s, and 3 indicating completion of semi-tandem testing and holding full-tandem stance between 3 to 10 s, and 4 indicating completion of full-tandem testing (Kasper, Freedman, & Niefeld, 2012).

For chair stands, participants started in a seated position with their arms crossed and were asked to rise from their seated position five times. If the task was completed five times, it was graded as a "pass," and the time taken to complete the task was recorded. If the task was not completed successfully all five times, it was graded as a "fail." Participants who did not attempt the chair stand activity, either due to safety concerns by the examiner or by the participant, received a "not attempted" score. Chair stand testing scores ranged from 0 to 4, where 0 was scored as not attempting the

Table 1. Design of Tiered Prediction Models for Falls and Recurrent Falls.

Model	Independent variables
Tier 1	Age, gender, race
Tier 2	Tier 1 + self-reported balance problem, history of fall
Tier 3	Tier 2 + medical conditions ^a
Tier 4	Tier 3 + SPPB score ^b

Note. SPPB = Short Physical Performance Battery; NHATS = National Health and Aging Trends Study.

^aHeart attack, heart disease, stroke, hypertension, diabetes, osteoporosis, vision impairment, and hearing impairment.

^bSummary score of performance on side-by-side, semi-tandem, and full-tandem stances, chair stands, and gait speed (Kasper & Freedman, 2014) using NHATS percentiles.

test or attempting and not completing the test, and 1 through 4 represented the quartiles of time taken to complete the test (4 = fastest; Kasper & Freedman, 2014).

For gait speed, participants were asked to walk 3 m twice, and the fastest time to complete this task was recorded. Participants were allowed to use assistive devices, such as canes or walkers, but were excluded from testing if they used a wheelchair or similar motorized device. Gait speed was scored by stratifying speed into quartiles from the total NHATS population. Scores ranged from 0 to 4, where 0 was scored as not attempting the test or attempting and not completing the test, and 1 through 4 represented the quartiles of gait speed (4 = fastest; Kasper & Freedman, 2014). The overall SPPB score represented the sum of the scores of the individual activities (Kasper & Freedman, 2014).

Outcome Variables of Interest

In Round 2, participants were asked whether they sustained a fall since the Round 1 interview. Falls were defined as “any fall, slip, or trip in which you lose your balance and land on the floor or ground or at a lower level.” “*Any fall*” was defined as an incident fall since the Round 1 interview. “*Recurrent falls*” was defined as answering “Yes” to the question “In the last 12 months, have you fallen down more than once?” Recurrent fallers may represent a distinct population compared with those who suffer a single fall (Nevitt, Cummings, Kidd, & Black, 1989; Tinetti et al., 1994): Recurrent fallers are more likely to have intrinsic risk factors for falls and problems with performance testing and mobility, and have higher fall-related complication rates (Nevitt et al., 1989; Pluijm et al., 2006). Separate prediction models were developed for “*any fall*” and “*recurrent falls*.”

Model Design

A tiered approach was used to generate a series of prediction models by sequentially adding variable groupings that progressed in clinical complexity, which allowed for evaluation of the relative contribution of each set of variables to the overall predictive power of

the model. The goal of this approach was to create the most parsimonious clinical model with the highest predictive power.

Table 1 shows the variables investigated in each tier. Tier 1 variables consisted of basic demographic data including age, gender, and race. Tier 2 variables additionally included problems with balance and coordination and history of fall. Tier 3 variables additionally included medical conditions including heart attack, coronary artery disease, stroke, diabetes, hypertension, osteoporosis, visual impairment, and hearing impairment. Tier 4 variables additionally included the SPPB test score. As gait speed is also commonly used as a stand-alone measure of physical performance and fall risk, we investigated the predictive ability of gait speed alone in a separate model (Abellan van Kan et al., 2009; Montero-Odasso et al., 2005; Stone, Skubic, Rantz, Abbott, & Miller, 2015).

Statistical Analysis

A cross-validation method was used for testing the prediction models. The study population was randomly divided into two cohorts: a model development cohort (two third of the study population, $n = 5,070$) and a validation cohort (one third of the study population, $n = 2,539$). Using the development sample, multivariate logistic regression models were constructed for each tier. Receiver operating characteristic (ROC) curve and area under the ROC curve (AUC) were created in R version 3.1.0 (R Core Team, 2013). All other statistical analyses were performed using Stata 13 (College Station, Texas). All analyses were weighted using variables provided by NHATS for strata, cluster, and sample weighting. The predicted probabilities of *any fall* or *recurrent falls* were used to construct ROC curves. AUCs were computed for evaluating the predictive performance of each tiered logistic regression model. We used the R function “withReplicates,” which is part of the survey package, to estimate replicate-weight-based variance for AUC (Lumley, 2004). An AUC of 0.50 implies that a model is as good in predictive value as chance alone, and a higher AUC implies stronger predictive power. The most parsimonious clinical model for

each outcome variable (*any fall* and *recurrent fall*) was then selected that maximized AUC with the fewest number of variables. The parameters of the logistic models from the development set were applied to the validation set to construct ROC curves and to calculate AUCs for testing the predictive value of the logistic models.

Results

Demographic characteristics and medical conditions of study participants and those who sustained incident *any fall* and *recurrent falls* are shown in Table 2. Overall, 32.9% (95% confidence interval [CI] = [31.6, 34.3]) of participants sustained a fall in the 12 months between Rounds 1 and 2, and 15.0% (95% CI = [14.1, 15.9]) experienced recurrent falls during this interval. In univariate analyses, females and older participants were significantly more likely to experience an incident fall, whereas Blacks were significantly less likely to experience a fall. Individuals with a previous history of falls, self-reported problems with balance and coordination, heart attack, coronary artery disease, stroke, diabetes mellitus, hypertension, and osteoporosis reported at baseline were significantly more likely to experience an incident fall. Recurrent falls were significantly more likely in individuals who were older, White, or Hispanic; had self-reported problems with balance and coordination; and had a history of falls, heart attack, heart disease, stroke, diabetes, hypertension, osteoporosis, and visual impairment reported at baseline.

Figure 1 shows the AUCs of the tiered prediction models for *any fall* and *recurrent falls* from the development set data. For *any fall*, the Tier 1 model and Tier 2 model had AUCs of 0.57 (95% CI = [0.54, 0.60]) and 0.69 (95% CI = [0.67, 0.71]), respectively. Incorporating Tier 3 variables did not significantly increase the AUC (0.71, 95% CI = [0.69, 0.73]) beyond that of the Tier 2 model. Similarly, addition of the SPPB score (AUC = 0.72, 95% CI = [0.70, 0.73]) also did not significantly increase the AUC beyond that of Tier 2. In the model that included only fastest gait speed, the AUC for *any fall* was 0.60 (95% CI = [0.57, 0.63]). For *recurrent falls*, the Tier 1 and 2 models had AUCs of 0.59 (95% CI = [0.56, 0.61]) and 0.77 (95% CI = [0.74, 0.79]), respectively. The AUC showed minimal improvement in Models 3 and 4 with AUCs of 0.78 (95% CI = [0.76, 0.80]) and 0.79 (95% CI = [0.76, 0.81]), respectively. In the model with gait speed alone, the AUC for *recurrent falls* was 0.65 (95% CI = [0.62, 0.68]).

Based on these results, the Tier 2 model was selected as the most parsimonious clinical prediction model that optimized AUC for both *any fall* and *recurrent falls*. The appendix shows the regression coefficients for the Tier 2 models for *any fall* and *recurrent falls*. The ROC curve derived from the development data set was then validated in the validation data set. A comparison of these ROC curves is shown in Figure 2 for both *any fall* and

recurrent falls. The ROC curves demonstrate a high degree of concordance between the development and validation samples, suggesting a strong external validity of the Tier 2 model prediction model.

To compare the most parsimonious model developed in this study with the existing fall-risk prediction models, we applied the parameters in the widely cited recurrent-fall-risk model developed by Stalenhoeft et al. to the NHATS study population. The Stalenhoeft model included the predictors age ≥ 80 years, female gender, ≥ 2 falls in the past year, depression, low grip strength, and abnormal postural sway (Stalenhoeft et al., 2002). Variables in the Stalenhoeft model were substituted with analogous NHATS variables where possible. Postural sway abnormality was not assessed in NHATS and was therefore not included in the recapitulated model. The AUC from the validation sample for the Stalenhoeft model was 0.64 for recurrent fallers in the NHATS population, which is lower than the AUC of 0.77 for recurrent fallers in the risk prediction model developed here.

Discussion

A model including demographic data and participant-reported fall history and balance problems predicted incident falls and recurrent falls with a high degree of accuracy in a community-dwelling older population of Medicare enrollees in the NHATS study. The results presented here demonstrate that for both *any fall* and *recurrent falls*, a prediction model using basic demographic data and two routine fall screening questions was performed as well as more complex models that included medical history and physical performance measures. These findings suggest that there is limited additional value in including physical performance testing in initial screening of fall risk in older community-dwelling individuals. Moreover, gait speed, which is a simple physical performance measure often assessed in clinical practice, did not improve the predictive ability of models that included only demographic and self-reported historical data alone. A more parsimonious falls prediction tool could reduce time and resource use, as well as the need for clinical expertise to administer physical performance tests.

The prediction model developed in this study could be useful to clinicians, given that elements of routinely collected patient data can identify those at high risk for falls and allow preventative intervention and risk factor modification. To illustrate the potential clinical utility of this prediction model, we considered two hypothetical older adults at low and high risk of falls based on the model variables. Mr. A, an example low-risk individual, is a 72-year-old Asian American male with no self-reported problems with balance or coordination, and no previous history of falls. Mrs. B, an example high-risk individual, is an 87-year-old Hispanic female who

Table 2. Baseline Clinical Characteristics of Round I Community-Dwelling NHATS Participants and Stratified by Fall Outcome.

Characteristic	NHATS (n = 7,609)	Any fall (n = 2,028)	p value ^b	Recurrent falls (n = 957)	p value ^b
	% [95% CI] ^a	% [95% CI] ^a		% [95% CI] ^a	
Overall		32.9 [31.6, 34.3]		15.0 [14.1, 15.9]	
Demographics					
Gender					
Male	43.4 [42.0, 44.8]	30.0 [28.0, 32.7] ^c	<.001	14.7 [13.4, 16.1] ^c	.62
Female	56.6 [55.2, 58.0]	35.2 [33.3, 37.0]		15.2 [13.9, 16.6]	
Age					
65-69	27.9 [27.0, 29.0]	29.6 [26.8, 32.5]	<.001	12.9 [11.2, 15.0]	<.001
70-74	25.0 [24.1, 25.8]	28.7 [26.0, 31.5]		12.5 [10.9, 14.3]	
75-79	19.1 [18.2, 19.9]	33.4 [30.2, 36.7]		13.1 [11.0, 15.6]	
80-84	14.7 [14.0, 15.4]	37.5 [35.1, 40.1]		18.0 [15.5, 20.7]	
85-89	9.1 [8.5, 9.8]	42.4 [38.2, 46.8]		23.6 [20.7, 26.8]	
90+	4.3 [3.8, 4.7]	43.6 [38.6, 48.7]		24.6 [20.7, 29.0]	
Race/ethnicity					
NH White	81.5 [79.7, 83.1]	33.8 [32.3, 35.4]	<.001	15.5 [14.4, 16.6]	<.001
NH Black	8.2 [7.4, 9.1]	27.1 [24.2, 30.2]		12.3 [10.6, 14.2]	
Other	3.5 [2.8, 4.5]	21.6 [15.2, 29.9]		5.4 [3.1, 9.2]	
Hispanic	6.8 [5.8, 7.9]	34.7 [29.5, 40.2]		16.9 [13.7, 20.1]	
Medical					
Self-reported problems with balance/coordination					
Yes	28.2 [26.8, 29.5]	51.7 [48.8, 54.6]	<.001	31.3 [28.8, 34.0]	<.001
No	71.8 [70.5, 73.2]	48.3 [45.4, 51.2]		9.0 [7.9, 10.1]	
History of falls ^d					
Yes	30.5 [29.4, 31.6]	50.7 [47.5, 53.9]	<.001	26.5 [23.7, 29.4]	<.001
No	69.5 [68.4, 70.6]	23.3 [21.8, 24.9]		7.4 [6.5, 8.3]	
Conditions					
Heart attack					
Yes	14.1 [13.1, 15.1]	42.5 [37.8, 47.2]	<.001	20.1 [17.9, 24.5]	<.001
No	85.9 [84.9, 86.9]	31.4 [30.0, 32.8]		14 [13.1, 15.0]	
Heart disease					
Yes	17.5 [16.5, 18.5]	42.3 [39.2, 45.6]	<.001	21.7 [19.5, 24.1]	<.001
No	82.6 [81.5, 83.5]	31.0 [29.6, 32.4]		13.6 [12.6, 14.6]	
Stroke					
Yes	10.0 [9.3, 10.9]	49.5 [44.6, 54.4]	<.001	26.0 [22.0, 30.4]	<.001
No	90.0 [89.2, 90.7]	31.1 [29.8, 32.5]		13.8 [12.8, 14.8]	
Diabetes					
Yes	23.9 [22.7, 25.1]	37.5 [35.0, 40.2]	<.001	19.5 [17.2, 21.9]	<.001
No	76.1 [74.9, 77.3]	31.5 [29.9, 33.1]		13.6 [12.6, 14.6]	
Hypertension					
Yes	63.9 [62.5, 65.3]	34.7 [32.9, 36.6]	.001	16.1 [14.9, 17.4]	.005
No	36.1 [34.7, 37.5]	29.7 [27.6, 31.8]		12.9 [11.4, 14.5]	
Osteoporosis					
Yes	21.2 [20.2, 22.2]	41.1 [37.7, 44.7]	<.001	20.1 [17.7, 22.8]	<.001
No	78.8 [77.8, 79.8]	30.7 [29.2, 32.3]		13.6 [12.6, 14.7]	
Vision					
Normal	38.4 [37.2, 39.7]	32.0 [29.5, 34.7]	.24	14.5 [12.7, 16.6]	.004
Corrective lenses	61.1 [59.9, 62.4]	33.3 [31.6, 35.0]		14.9 [13.9, 16.0]	
Blind	0.43 [0.31, 0.59]	47.4 [31.8, 63.6]		41.0 [24.9, 59.3]	
Hearing					
Normal	88.1 [87.2, 88.9]	32.4 [31.0, 33.8]	.090	14.5 [13.5, 15.5]	.121
Hearing aides	11.7 [10.8, 12.6]	36.6 [33.2, 40.0]		17.9 [15.0, 21.3]	
Deaf	0.2 [0.1, 0.4]	30.5 [11.3, 60.1]		18.4 [4.0, 55.0]	
Physical performance testing					
Gait speed ^e					
0	9.0 [8.1, 9.9]	47.4 [43.4, 51.4]	<.001	26.5 [22.6, 30.8]	<.001
1	11.0 [10.0, 12.1]	42.4 [39.4, 45.5]		23.2 [20.9, 25.8]	
2	17.1 [15.9, 18.3]	32.8 [29.7, 36.2]		14.2 [11.9, 16.7]	
3	24.9 [23.7, 26.1]	27.5 [24.4, 30.8]		10.3 [8.5, 12.4]	
4	38.1 [36.2, 39.9]	23.7 [20.2, 27.6]		8.4 [6.6, 10.8]	
SPPB score ^f					
0	7.3 [6.5, 8.2]	46.8 [41.5, 52.2]	<.001	27.5 [22.5, 33.2]	<.001
1	1.9 [1.7, 2.2]	58.4 [47.9, 68.2]		34.6 [25.2, 45.4]	
2	2.7 [2.3, 3.2]	50.9 [45.5, 56.2]		28.4 [23.6, 33.7]	
3	2.9 [2.6, 3.3]	45.6 [39.6, 51.7]		27.3 [22.0, 33.3]	
4	3.1 [2.7, 3.6]	36.2 [30.1, 42.8]		15.5 [11.5, 20.5]	
5	3.6 [3.1, 4.1]	41.8 [37.0, 46.8]		20.8 [17.4, 24.8]	

(continued)

Table 2. (continued)

Characteristic	NHATS (n = 7,609)	Any fall (n = 2,028)	p value ^b	Recurrent falls (n = 957)	p value ^b
	% [95% CI] ^a	% [95% CI] ^a		% [95% CI] ^a	
6	4.7 [4.1, 5.4]	34.3 [28.7, 40.4]		15.6 [11.6, 20.7]	
7	5.9 [5.3, 6.6]	32.3 [27.2, 37.8]		12.3 [9.5, 15.8]	
8	8.0 [7.2, 8.9]	27.5 [22.3, 33.3]		9.5 [6.7, 13.4]	
9	9.8 [9.1, 10.5]	20.0 [16.9, 23.6]		6.5 [4.6, 9.1]	
10	12.7 [11.7, 13.7]	21.0 [16.9, 25.7]		8.3 [5.7, 12.0]	
11	16.7 [15.5, 18.1]	28.8 [23.0, 35.5]		9.2 [6.1, 13.7]	
12	20.7 [19.4, 22.1]	19.1 [13.3, 26.5]		7.5 [5.9, 9.5]	

Note. NHATS = National Health and Aging Trends Study; CI = confidence interval; NH = non-Hispanic; SPPB = Short Physical Performance Battery.

^aWeighted frequency, since Round 1 interview.

^bPearson's chi-square.

^cRow percentages were used for analysis. For example, 30.0% of Round 1 NHATS males experienced "any fall" and 14.7% experienced "recurrent falls."

^dHistory of falls were assessed at the onset of NHATS Round 1 interviews and defined as having fallen in the preceding 12 months.

^eGait speed was assessed using fastest time taken for participant to walk 3 m from two trials. This velocity was stratified into quartiles for the NHATS population, with 0 indicating the test was not completed or attempted; and 1 to 4 corresponding to increasing quartiles of performance, with a score of 4 representing best performances.

^fSPPB testing was assessed through the three domains of balance testing (side-by-side, semi-tandem, full-tandem), walking speed, and repeated chair stands. Walking speed and repeated chair stands were scored according to increasing quartiles of performance, with 0 indicating the test was not completed or attempted, and 1 to 4 corresponding to increasing quartiles of performance. Balance testing was scored as follows: 0 (tests were not attempted); 1 (completion of only side-by-side testing without completion of semi-tandem testing); 2 (completion of semi-tandem testing and either not attempting or holding full-tandem for less than 2.99 s); 3 (completion of semi-tandem testing and holding full-tandem from between 3 s to 9.99 s); 4 (completion of full-tandem testing). Completion of a balance stance required holding that stance for 10 s.

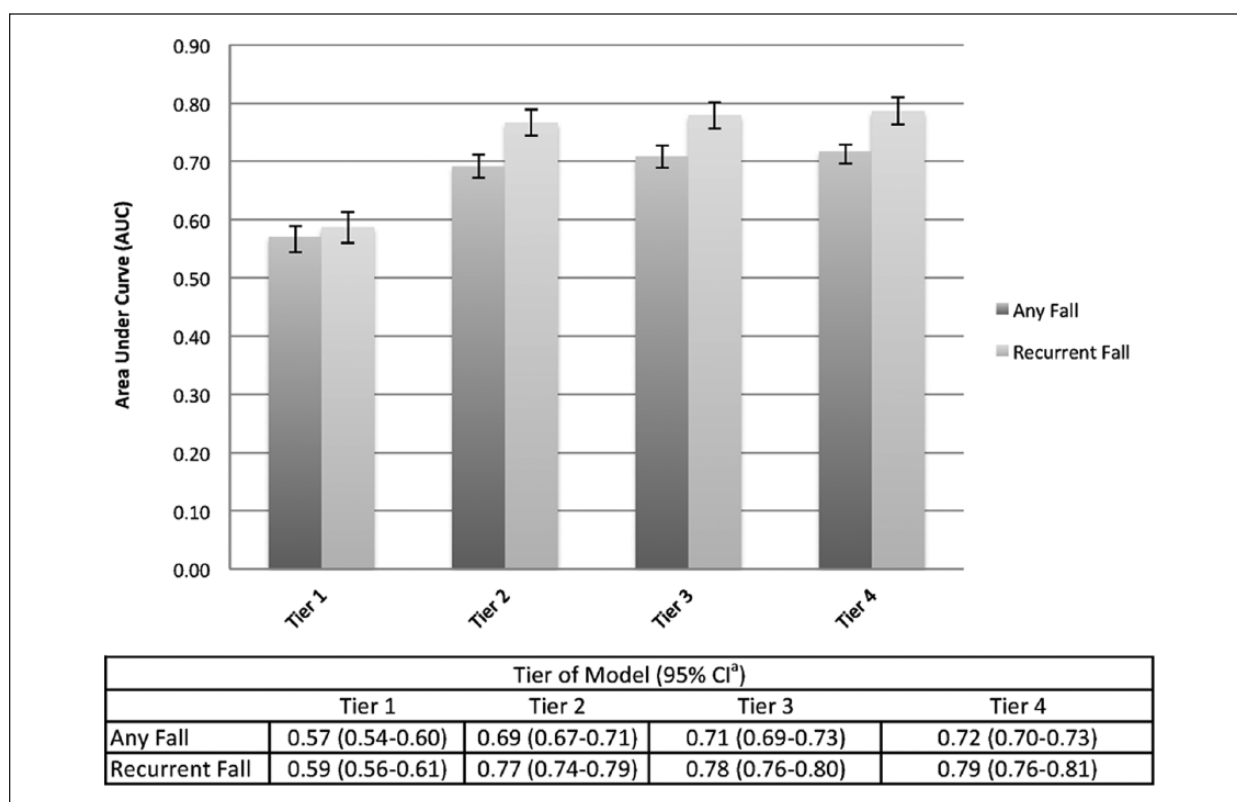


Figure 1. Risk models for the prediction of falls and recurrent falls using development set data.

Note. AUC comparison for progressive model tiers for falls and recurrent falls in the development set population (two thirds of overall NHATS population, n = 5,070). AUC = area under curve; NHATS = National Health and Aging Trends Study.

^aConfidence interval.

sustained an accidental fall at home 2 years ago and endorses self-reported problems with balance and coordination due to occasional light-headedness. Using the regression model coefficients in the appendix, Mr. A has

predicted probabilities of *any fall* and *recurrent falls* of .12 and .02, respectively, whereas Mrs. B has predicted probabilities of *any fall* and *recurrent falls* of .72 and .54, respectively.

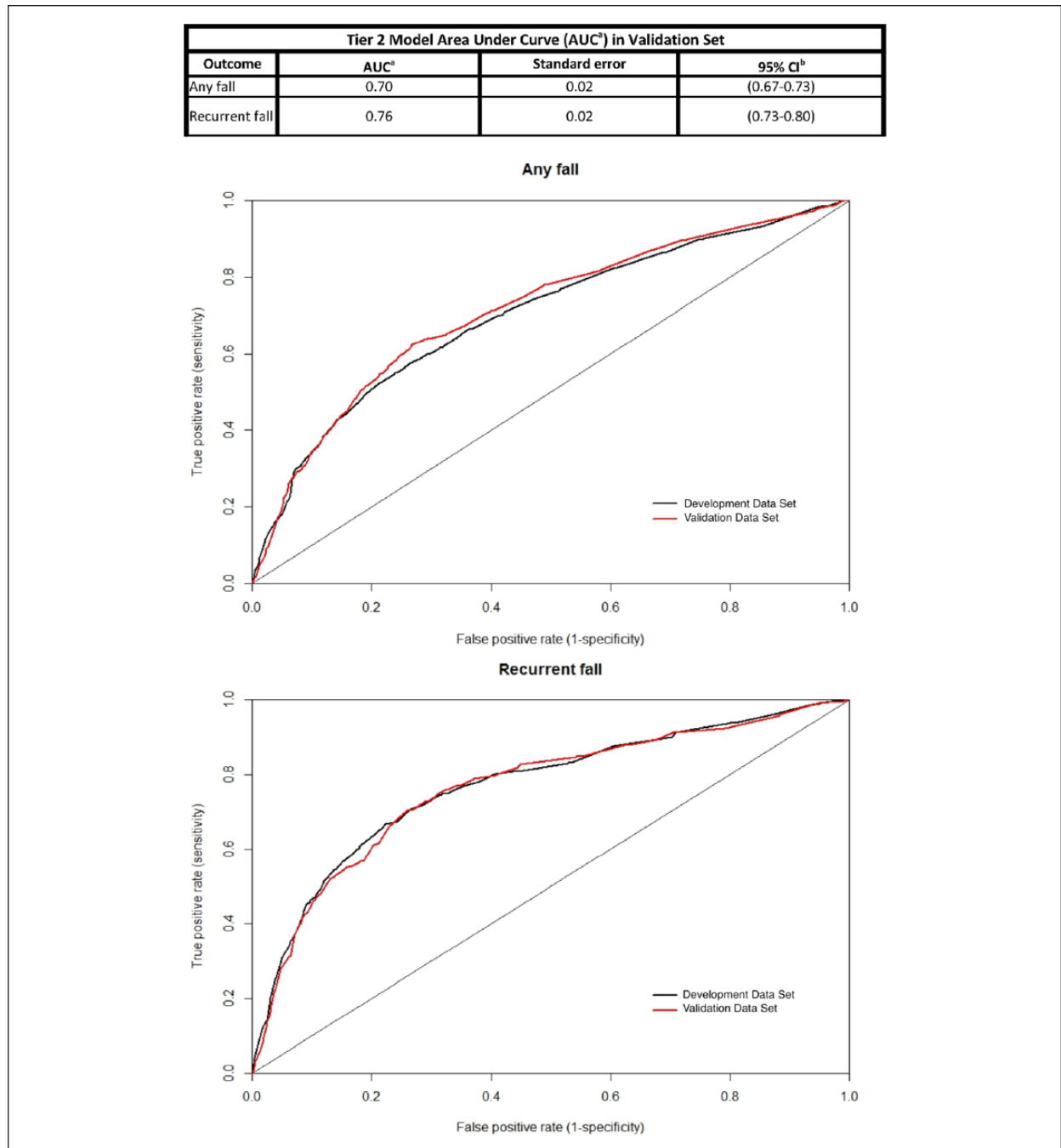


Figure 2. Tier 2 model ROC curves and AUC in validation set.

Note. ROC curves, and their respective AUC for the Tier 2 model validated in the one third of the overall study population ($n = 2,539$) not included in the model development population ($n = 5,070$). ROC curve for model development population (black) and validation population (red) are shown. ROC = receiver operator characteristic.

^aArea under curve.

^bConfidence Interval.

In this study, we extended the work of previous investigators by developing a falls prediction model using a nationally representative prospective sample of community-dwelling older individuals. Furthermore, this study expands on existing fall prediction models through sequential analysis of the marginal contribution of variable sets to the model's predictive power and

through validation of the model in an independent sample. In contrast to previous risk models, the models developed here are predictive of both overall falls and recurrent falls. We observed AUCs for the ROC curves of 0.69 and 0.77 for *any fall* and *recurrent falls*, respectively. These AUC values are within the range of values reported in other studies that studied prospective fall

risk using prediction models of varying complexity (Lord et al., 2003; Pluijm et al., 2006; Stalenhoef et al., 2000; Stalenhoef et al., 2002). When we compared our Tier 2 model specifically with the Stalenhoef et al. prediction model for recurrent falls, our model fared favorably. Further limitations of the Stalenhoef et al. model include the small sample size ($N = 311$) and lack of true validation in an independent population, which may limit the generalizability of their findings. In addition, the model necessitates physical performance testing that may require specific clinical expertise, dedicated time, and resource commitments (Stalenhoef et al., 2002). Similarly, Lord et al developed a model to predict recurrent fall risk based on the physiological profile assessment (PPA), a series of physical assessments that test vision, peripheral sensation, muscle strength, reaction time, and postural sway. However, administering the PPA is time intensive, and appears to require specially trained personnel to validly and reliably administer the PPA (Lord et al., 2003).

We note several limitations of this study. Although the NHATS sample was designed to be nationally representative in the contiguous United States, the applicability of these findings to older individuals in other countries and health care systems is unclear. Although physical performance testing was included in the higher tier models, it is possible that other physical performance maneuvers not included in NHATS testing could substantially improve the predictive power of the fall-risk models. In addition, the medical conditions included in this study were

limited to those in the NHATS study and did not include other fall-risk factors, such as muscle weakness or polypharmacy, which may be relevant to fall risk. Furthermore, the outcome variables (fall and recurrent falls) were ascertained based on self-report, which may be subject to recall bias (Centers for Disease Control and Prevention, 2008). Finally, the Tier 2 model did not include physical performance measures, which could provide some insight into the mechanism of fall risk and could help guide treatment. We suggest that individuals identified to be at high risk of falls based on the Tier 2 model should undergo further evaluation with assessments such as the SPPB to identify potential targets for intervention (e.g., decreased lower extremity strength).

Conclusion

Clinical prediction models for falls and recurrent falls were developed from a nationally representative sample of community-dwelling older individuals. A clinically parsimonious model consisting of participant demographic data and self-reported balance or coordination problems and previous history of falls demonstrated similar predictive power as more complex models that included medical history and physical performance testing. These findings suggest that a simplified screening protocol may be just as effective in identifying individuals at risk for falls as physical performance-based algorithms while being more accessible for routine office-based implementation.

Appendix

Risk model for the prediction of falls and recurrent falls from Tier 2 model using training data.

Predictors	Fall				Recurrent fall			
	coefficient	SE	OR	95% CI	coefficient	SE	OR	95% CI
Age								
70-74	-0.03	0.14	0.97	0.74-1.26	-0.06	0.16	0.95	0.69-1.29
75-79	0.07	0.15	1.07	0.80-1.44	-0.08	0.16	0.93	0.67-1.27
80-84	0.17	0.13	1.18	0.92-1.52	0.11	0.15	1.11	0.84-1.48
85-89	0.37*	0.14	1.45	1.11-1.91	0.49**	0.15	1.63	1.21-2.18
90+	0.26	0.21	1.3	0.87-1.95	0.47*	0.19	1.61	1.11-2.32
Gender								
Female	0.12	0.08	1.13	0.96-1.32	-0.22*	0.1	0.8	0.65-0.97
Race								
Black	-0.27*	0.11	0.76	0.61-0.95	-0.27*	0.12	0.77	0.60-0.98
Other	-0.52	0.29	0.59	0.34-1.05	-0.99	0.53	0.37	0.13-1.05
Hispanic	0.07	0.17	1.08	0.76-1.51	0.02	0.19	1.02	0.70-1.50
Self-reported balance problem	0.69***	0.08	1.99	1.69-2.34	1.11	0.1	3.04	2.49-3.70
Fall history	1.15***	0.09	3.15	2.65-3.74	1.46***	0.1	4.29	3.52-5.22
Intercept	-1.44	0.11			2.67	0.14		

Note. Age range of 65 to 69, male gender, and White race were used as reference categories (OR = 1.0) for age, gender, and race, respectively. SE = standard error; OR = odds ratio; CI = confidence interval.

* $p < .05$. ** $p < .01$. *** $p < .001$.

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References

- Abellan van Kan, G., Rolland, Y., Andrieu, S., Bauer, J., Beauchet, O., Bonnefoy, M., . . . Vellas, B. (2009). Gait speed at usual pace as a predictor of adverse outcomes in community-dwelling older people: An International Academy on Nutrition and Aging (IANA) Task Force. *The Journal of Nutrition, Health & Aging, 13*, 881-889.
- Ayoung-Chee, P., McIntyre, L., Ebel, B. E., Mack, C. D., McCormick, W., & Maier, R. V. (2014). Long-term outcomes of ground-level falls in the elderly. *The Journal of Trauma and Acute Care Surgery, 76*, 498-503; discussion 503. doi:10.1097/TA.0000000000000102
- Berg, K. (2009). Measuring balance in the elderly: Preliminary development of an instrument. *Physiotherapy Canada, 41*, 304-311.
- Berg, K. O., Wood-Dauphinee, S. L., Williams, J. I., & Maki, B. (1992). Measuring balance in the elderly: Validation of an instrument. *Canadian Journal of Public Health/Revue Canadienne De Santé Publique, 83*(Suppl. 2), S7-11.
- Brauer, C. A., Coca-Perraillon, M., Cutler, D. M., & Rosen, A. B. (2009). Incidence and mortality of hip fractures in the United States. *Journal of the American Medical Association, 302*, 1573-1579. doi:10.1001/jama.2009.1462
- Centers for Disease Control and Prevention. (2008). Self-reported falls and fall-related injuries among persons aged > or =65 years—United States, 2006. *Morbidity and Mortality Weekly Report, 57*, 225-229.
- Covinsky, K. E., Kahana, E., Kahana, B., Kercher, K., Schumacher, J. G., & Justice, A. C. (2001). History and mobility exam index to identify community-dwelling elderly persons at risk of falling. *The Journals of Gerontology, Series A: Biological Sciences & Medical Sciences, 56*, M253-M259.
- Deandrea, S., Lucenteforte, E., Bravi, F., Foschi, R., La Vecchia, C., & Negri, E. (2010). Risk factors for falls in community-dwelling older people: A systematic review and meta-analysis. *Epidemiology (Cambridge, Mass.), 21*, 658-668. doi:10.1097/EDE.0b013e3181e89905
- Dunn, J. E., Rudberg, M. A., Furner, S. E., & Cassel, C. K. (1992). Mortality, disability, and falls in older persons: The role of underlying disease and disability. *American Journal of Public Health, 82*, 395-400.
- Freire, A. N., Guerra, R. O., Alvarado, B., Guralnik, J. M., & Zunzunegui, M. V. (2012). Validity and reliability of the Short Physical Performance Battery in two diverse older adult populations in Quebec and Brazil. *Journal of Aging and Health, 24*, 863-878. doi:10.1177/0898264312438551
- Godi, M., Franchignoni, F., Caligari, M., Giordano, A., Turcato, A. M., & Nardone, A. (2013). Comparison of reliability, validity, and responsiveness of the mini-BESTest and Berg Balance Scale in patients with balance disorders. *Physical Therapy, 93*, 158-167. doi:10.2522/ptj.20120171
- Gómez, J. F., Curcio, C.-L., Alvarado, B., Zunzunegui, M. V., & Guralnik, J. (2013). Validity and reliability of the Short Physical Performance Battery (SPPB): A pilot study on mobility in the Colombian Andes. *Colombia Médica (Cali, Colombia), 44*, 165-171.
- Guralnik, J. M., Simonsick, E. M., Ferrucci, L., Glynn, R. J., Berkman, L. F., Blazer, D. G., . . . Wallace, R. B. (1994). A Short Physical Performance Battery assessing lower extremity function: Association with self-reported disability and prediction of mortality and nursing home admission. *Journal of Gerontology, 49*, M85-M94.
- Hartholt, K. A., van Beeck, E. F., Polinder, S., van der Velde, N., van Lieshout, E. M. M., Panneman, M. J. M., . . . Patka, P. (2011). Societal consequences of falls in the older population: Injuries, healthcare costs, and long-term reduced quality of life. *The Journal of Trauma, 71*, 748-753. doi:10.1097/TA.0b013e3181f6f5e5
- Hendrie, D., Hall, S. E., Arena, G., & Legge, M. (2004). Health system costs of falls of older adults in Western Australia. *Australian Health Review: A Publication of the Australian Hospital Association, 28*, 363-373.
- Johnson, C. E., Danhauer, J. L., Koch, L. L., Celani, K. E., Lopez, I. P., & Williams, V. A. (2008). Hearing and balance screening and referrals for Medicare patients: A national survey of primary care physicians. *Journal of the American Academy of Audiology, 19*(2), 171-190.
- Kasper, J., & Freedman, V. (2014). *National Health and Aging Trends Study user guide: Rounds 1 & 2, final release*. Baltimore, MD: Johns Hopkins University School of Public Health.
- Kasper, J., Freedman, V., & Niefeld, M. (2012). *Construction of performance-based summary measures of physical capacity in the National Health and Aging Trends Study (NHATS Technical Paper #4)*. Baltimore, MD: Johns Hopkins University School of Public Health.
- Legters, K. (2002). Fear of falling. *Physical Therapy, 82*, 264-272.
- Lord, S. R., Menz, H. B., & Tiedemann, A. (2003). A physiological profile approach to falls risk assessment and prevention. *Physical Therapy, 83*, 237-252.
- Lumley, T. (2004). Analysis of complex survey samples. *Journal of Statistical Software, 9*(8), 1-19.
- Major, M. J., Fatone, S., & Roth, E. J. (2013). Validity and reliability of the Berg Balance Scale for community-dwelling persons with lower-limb amputation. *Archives of Physical Medicine and Rehabilitation, 94*, 2194-2202. doi:10.1016/j.apmr.2013.07.002
- Montaquila, J., Freedman, V., Spillman, B., & Kasper, J. (2012). *National Health and Aging Trends Study Development of Round 1 Survey Weights* (NHATS Technical Paper #2). Baltimore, MD: Johns Hopkins University School of Public Health.
- Montaquila, J., Freedman, V., Vicki, A., Spillman, B., & Kasper, J. (2014). *National Health and Aging Trends Study Development of Round 2 Survey Weights* (NHATS Technical Paper #6). Baltimore, MD: Johns Hopkins University School of Public Health.
- Montero-Odasso, M., Schapira, M., Soriano, E. R., Varela, M., Kaplan, R., Camera, L. A., & Mayorga, L. M. (2005).

- Gait velocity as a single predictor of adverse events in healthy seniors aged 75 years and older. *The Journals of Gerontology, Series A: Biological Sciences & Medical Sciences*, 60, 1304-1309.
- Nevitt, M. C., Cummings, S. R., Kidd, S., & Black, D. (1989). Risk factors for recurrent nonsyncopal falls: A prospective study. *Journal of the American Medical Association*, 261, 2663-2668.
- Peeters, G., van Schoor, N. M., & Lips, P. (2009). Fall risk: The clinical relevance of falls and how to integrate fall risk with fracture risk. *Best Practice & Research Clinical Rheumatology*, 23, 797-804. doi:10.1016/j.berh.2009.09.004
- Pluijm, S. M. F., Smit, J. H., Tromp, E. A. M., Stel, V. S., Deeg, D. J. H., Bouter, L. M., & Lips, P. (2006). A risk profile for identifying community-dwelling elderly with a high risk of recurrent falling: Results of a 3-year prospective study. *Osteoporosis International: A Journal Established as Result of Cooperation between the European Foundation for Osteoporosis and the National Osteoporosis Foundation of the USA*, 17, 417-425. doi:10.1007/s00198-005-0002-0
- R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Available from <http://www.R-project.org>
- Russell, M. A., Hill, K. D., Day, L. M., Blackberry, I., Gurrin, L. C., & Dharmage, S. C. (2009). Development of the Falls Risk for Older People in the Community (FROP-Com) screening tool. *Age and Ageing*, 38, 40-46. doi:10.1093/ageing/afn196
- Stalenhoef, P. A., Diederiks, J. P. M., Knottnerus, J. A., de Witte, L. P., & Crebolder, H. F. (2000). The construction of a patient record-based risk model for recurrent falls among elderly people living in the community. *Family Practice*, 17, 490-496.
- Stalenhoef, P. A., Diederiks, J. P. M., Knottnerus, J. A., Kester, A. D. M., & Crebolder, H. F. J. M. (2002). A risk model for the prediction of recurrent falls in community-dwelling elderly: A prospective cohort study. *Journal of Clinical Epidemiology*, 55, 1088-1094.
- Stevens, J. A., Corso, P. S., Finkelstein, E. A., & Miller, T. R. (2006). The costs of fatal and non-fatal falls among older adults. *Injury Prevention: Journal of the International Society for Child and Adolescent Injury Prevention*, 12, 290-295. doi:10.1136/ip.2005.011015
- Stone, E., Skubic, M., Rantz, M., Abbott, C., & Miller, S. (2015). Average in-home gait speed: Investigation of a new metric for mobility and fall risk assessment of elders. *Gait & Posture*, 41, 57-62. doi:10.1016/j.gaitpost.2014.08.019
- Tinetti, M. E. (2003). Clinical practice. Preventing falls in elderly persons. *The New England Journal of Medicine*, 348, 42-49. doi:10.1056/NEJMc020719
- Tinetti, M. E., Baker, D. I., McAvay, G., Claus, E. B., Garrett, P., Gottschalk, M., . . . Horwitz, R. I. (1994). A multifactorial intervention to reduce the risk of falling among elderly people living in the community. *The New England Journal of Medicine*, 331, 821-827. doi:10.1056/NEJM199409293311301
- Vasunilashorn, S., Coppin, A. K., Patel, K. V., Lauretani, F., Ferrucci, L., Bandinelli, S., & Guralnik, J. M. (2009). Use of the Short Physical Performance Battery Score to predict loss of ability to walk 400 meters: Analysis from the InCHIANTI study. *The Journals of Gerontology, Series A: Biological Sciences & Medical Sciences*, 64, 223-229. doi:10.1093/gerona/gln022