Predicting Falls or Fall-Related Injuries within 3 Months of Emergency Department Discharge among Community-Dwelling Older Adults: A Comparison of 4 Screening Tools

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Possible Title:
Machine Learning-Aided Detection of Falls within 3 Months of Emergency Department Discharge Using Smartphone Accelerometer Data Among Community-Dwelling Older Adults

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BACKGROUND: Falls are the leading cause of injuries in older adults. Identifying older adults with risk for falls prior to discharge home from the Emergency Department (ED) could help direct fall prevention interventions, yet ED-based tools to assist risk stratification are under-developed. The aim of this study was to compare the performance of 4 different screening tools to predict future falls in the 90-days post ED discharge for older adults.

METHODS: A prospective cohort of community-dwelling adults age 60 years and older were recruited from two urban EDs prior to discharge (N=134). Participants completed the following in the ED: a single item screen for mobility (SIS-M), the 12-item Stay Independent Questionnaire (SIQ-12), and the Timed Up and Go test (TUG) while wearing a smartphone affixed to the lower back collecting 3-axis accelerometer data at 100 Hz. Falls after ED discharge were defined through self-report of any fall at 1- and 3-months and medical record review of ED or hospital encounter for fall-related injury 3-months post-discharge. We developed a hybrid-convolutional recurrent neural network (HCRNN) model of kinematic gait and balance characteristics using truncal 3-axis accelerometry collected during the TUG. We compared performance of M-SIS, FRQ, TUG time, and HCRNN by calculating the area under the receiver operating characteristic curve (AUC). Internal validation was conducted using bootstrap resampling with 1000 iterations for SIS-M, FRQ, and GUG and leave-one-out for the HCRNN.

RESULTS: 14 (10.4%) of participants met our primary outcome of a fall or fall-related injury within 90 days. The SIS-M had a AUC of 0.42 [95% confidence inteveal (CI) 0.19-0.65]. The SIQ-12 score had an AUC of 0.64 [95% confidence inteveal (CI) 0.49-0.80]. The TUG had an AUC of 0.48 (95% CI 0.29-0.68). The HCRNN model using generated accelerometer features collected dueing the TUG had an AUC of 0.99 (95% CI 0.98-1.00).

CONCLUSION: We found that standard screening tools lack sufficient accuracy to be used in isolation in the ED. A neural network model using generated accelerometer features collected during the TUG in the ED could be a promising modality but research is needed to externally validate these findings.

INTRODUCTION

Falls are common in older adults[1], result in significant morbidity and mortality[2], and cost~~s~~ the US health care system 50 billion dollars each year[3]. Targeted interventions can reduce rates of falls among older adults. For example, a recent review found that interventions can result in 25–30% reductions in falls for community-dwelling older adults one-year post-program.[4] Timely identification of older adults at-risk for falls is to connect them with effective fall prevention interventions is necessary but challenging.

To improve the identification of older adults at higher risk for falls, the Centers for Disease Control and Prevention (CDC) and the American Geriatric Society recommend yearly fall assessment screening for all adults 65 years of age and older.[5,6] Still, many older adults may not have this routine screening in primary care.[7,8] Identifying older adults in alternative care settings like the emergency department (ED) may help fill this gap in fall prevention.

The ED is a common site for older adults to seek care. Using nationally represen~~a~~tative US data from 2014–2017, 43% of persons aged 60 and over had an ED visit in a given year which increased with age.[9] The American College of Emergency Physician (ACEP) guidelines recommends routine identification of older adults at risk for falls[10]. Numerous tools for assessing fall risk among community-dwelling older adults have been tested in other settings, with area under the curves (AUCs) ranging from 0.49 to 0.87 in development models.[11] Yet, as noted by Carpenter et al.[12], existing ED-based screening tools are under~~-~~developed.

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The aim of this study was to compare the discriminatory performance of 4 different screening tools to predict future falls or fall-related injuries in the 90-days after ED discharge for community-dwelling older adults. We chose to study screening tools of increasing complexity to identify the most parsimonious model and allow comparisons across tools using self-reported risks versus functional task performance. Rapid and easy to perform tools are especially important in the ED, where surveys show that while most ED providers support screening older adults for fall risk, around half are unwilling to spend more than 2 minutes on screening.[13] We chose to assess kinematic characteristics of gait and balance during a functional task as a fall predictor given prior work in other settings showing that machine learning algorithms of accelerometer-based kinematic data can predict falls in older adults[14,15]. Findings from this study are critical to building a scientific evidence base for tools to identify older adults being discharged from the ED who could benefit from interventions to reduce falls and related injuries.

METHODS

We recruited a convenience sample of participants from May 9, 2019 and October 28, 2019. Recruitment occurred primarily during weekdays (approximately 11AM–5PM) based on research associate (RA) availability. We conducted phone call follow-ups at 1- and 3-months post-enrollment and medical record review to assess fall-related care at 3-month follow-up. The reporting of the study followed the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement.[16] The TRIPOD checklist is available in Additional file in the Appendix. Institutional Review Board approval for this study was granted by the University of Pittsburgh.

Source of Data

This study was conducted among patients who presented for care to two EDs within a single hospital system in Pittsburgh, PA.

Participants

An RA identified potential participants using the electronic ED tracking board based on age (i.e. 60+) and asked a member of the treating clinical ED team to refer only patients who are medically stable, community-dwelling, able to provide informed consent, who ambulate without ambulation aid, and who are being discharged to home. We focus solely on discharged ED patients as they do not have access to traditionaly inpatient screening and geriatric assessments. A member of the treating clinical team asked potential participants about their interest in participating in research. If the patient agreed, an RA confirmed eligibility criteria, including the ability to ambulate unassisted, and if met, completed informed consent.

Procedures

After consent was obtained, the participant was asked to complete a brief questionnaire and complete the Timed Up and Go test (TUG) while wearing a smartphone affixed to the lower back (i.e. midline L4) collecting 3-axis accelerometer data from 3-axes (i.e. mediolateral (ML), vertical (V), and anterior-posterior (AP) directions) at 100 Hz using the phyphox app (www.phyphox.org). We chose the TUG and lower back as the ideal location for sensor data capture based on best-practice recommendations.[17]

Outcome

The primary outcome for prediction was any fall or fall-related care encounter within 3 months, defined by either self-report of a fall at 1- or 3-months or medical record documentation of a fall-related ED or hospitalization care visit within 3-months post-enrollment. We chose to include both self-reported falls and fall-related injuries as we believe that both are clinically relevant for prevention efforts. We chose 3-months as our primary outcome assessment period as it is a time period where risks identified in the ED could be mechanistically relevant to a fall. The outcome assessor was blinded to predictors. <u>Phone follow-ups</u>: Consistent with international consensus recommendations, we defined self-reported falls as “an unexpected event in which the participants come to rest on the ground floor or lower level”.[18] <u>Medical record review</u>: We first identified all ED and hospitalization encounters that occurred between the day after enrollment and 90 days post-enrollment. We then inspected ED and hospitalization records to identify fall-related care, defined as encounters where an individual has an ICD-10 code (W00-

W19) or the term “fall” in the nursing or physican history with related injury, based on ICD-10 code of injury (S00-S99).[19]

Predictors

We examined 3 screening tools previously developed in other settings (i.e. Single Item Screen for Mobility (SIS-M); the Stay Independent Questionnaire (SIQ); Timed Up and Go (TUG)) and one tool we developed using a hybrid-convolutional recurrent neural network (HCRNN) model of truncal 3-axis accelerometry during the TUG. We chose these self-reported screening tools as they incorporated features found to be useful in other settings to predict falls in older adults.[20] The self-reported screening tools (i.e. SIS-M and FRQ) were completed in interview format in the ED and the instrumented TUG was performed prior to ED discharge. The research associate who assisted with collecting these predictors was blind to outcomes.

The SIS-M was taken from the EQ-5D-5L screening tool[21], one of the most common tools to measure health-related quality of life among older adults[22] and previously found to be sensitive to discriminate falls among community-dwelling older adults[23]. Participants were asked: “How would you describe your mobility TODAY”, with response options including: “no problems”, “slight problems”, “moderate problems”, “severe problems, and “I am unable to walk”. For the purposes of this study, we use any response other than “no problem” as positive.

The SIQ was developed by the CDC as part of an initiative to encourage and facilitate falls screening and management in primary care.[24] The algorithm begins with a 12-question patient self-assessment: https://www.cdc.gov/steadi/pdf/STEADI-Brochure-StayIndependent-508.pdf). According to published guidelines, a score of 4 or more or an affirmative response to any of three key questions (falling in the last year, being worried about falling, or feeling unsteady)[25] indicates fall risk. For the purpose of this study, we examined both the total score on 12-question survey and 3-question screen (yes/no) as predictors.

The TUG was developed 20 years ago to evaluate mobility in older adults[26] and consists of the time it takes for the patient to rise from an armed chair, walk 3 metres at their usual speed and with their usual gait aid, turn and return to the seated position in the chair. We chose the TUG as our functional test as it captures a wide range of kinematic movements yet can be completed in the ED setting. In a recent systematic review, a TUG time of >13.5 sec was found to have a pooled sensitivity of 0.31 (95% CI 0.13-0.57) and specificity of 0.74 (95% CI 0.52-0.88) to predict falls in community-dwelling older adults.[27] In the ED, the TUG was been found to be strongly associated with frailty but not necessarily falls after ED discharge among community-dwellling older adults after minor trauma.[28] For the purposes of this study, to allow for comparison with other ordinal scores, we batched TUG times into 4 second intervals.

For the HCRNN model of kinematic characteristics of gait and balance during the TUG, we first parsed the accelerometer data into 5 segments: (1) Stand up from the sitting position. (2) Walk 3 metres forward. (3) Turn around 180 degrees. (4) Walk 3 metres back to their original location. (5) Sit down on the chair. Signals were filtered through a fifth-order, low pass Butterworth filter with a 12.5 Hz cut-off frequency. Walking segments: For segments 2 & 4, we segmented the coded walking segments into windows of 1-second, each with a 50% overlap between two consecutive windows[29] and calculated features (e.g. mean, maximum, standard deviation, the maximum difference, pair-wise correlation, pair-wise covariance of the acceleration signals and harmonic ratio).[30] Sit/Stand segments: For segments 1 and 5, we computed the the maximum slope of the antero-posterior triangle, 2) the minimum slope of the AP triangle, and 3) the acceleration peak of the antero-posterior triangle.[31] Turn segment: For segment 3, we computed the step frequency by calculating the frequency peak from the power spectral density of the medio-lateral signal. For the purposes of this study, we examined a model using only the raw 3-axis accelerometer signals and another model using the 24 generated features found to have a p-value<0.05 on the Wald test.

Sample size

The study size was based on our goal of having at least 10 individuals with a fall outcome over 3-months follow-up. We based this on the “rule of thumb” of having at least 10 outcomes per predictor in a logistic regression model.[32] We estimated that 11% of older ED patients discharged to home would meet this endpoint at 3-months based on prior national estimates[33], thus resulting in a goal to have at least 90 participants with complete outcome data.

Missing data

We did not have any missing predictor data. For outcomes, 91/134 (67.9%) of participants provided self-reported fall outcome data at 1-month and 75/134 (56%) at 3-months. We were able to access medical records to assess any fall-related visits on all patients, therefore based on our composite fall outcome definition, had no need to impute data.

Statistical Analyses

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We first examined the univariate association between baseline sociodemographics and each question within the SIQ-12 and the primary outcome of fall at 3-months, presented as odds ratios (ORs) with 95% confidence intervals (CIs). We examined the univariate association between TUG acceleration sigmal amplitude features and falls using Student t-tests. We then used Receiver Operator Curves (ROC) to identify the optimal cutoff accuracy for the SIS-M, SIQ-12, and TUG, presenting sensitivity (Sens), specificity (Spec), positive likelihood ratios (LR+) and negative likelihood ratios (LR-) at key cutpoints. Internal validation was conducted using bootstrap (BS) resampling with 1000 iterations for SIS-M, FRQ, and TUG, and we present area under the curve (AUC) for both original ROC and BS-ROC curves. These analyses were completed using Stata 15.0.

Our HCRNN used several convolutional layers with filters from 64 to 512 (increasing by a factor of 2), separated by batch normalization layers and max-pooling layers, and then a bidirectional Long Short Term Memory layer with 128 units, dropout layer, and dense layer[29]. We used a leave-one-out model for testing, meaning that for each participant in the study we trained on all the other participants. During the classifier's learning or training process, we ran 10-fold cross-validation on this training group to find the model's best parameters. Then, we tested the model on the participant that was left out of the training. We calculated and reported the Sens, Spec, and ROC AUC for both the raw 3-axis accelerometer signals and another model using the 24 generated features These analyses were completed using *tensorflow* and *keras* in R.

RESULTS

Participants

During the study period, 220 community-dwelling older adults (60+ years) were identified by age using the ED tracking board, and 169 (76.9%) were assessed for eligibility from which we included 134 in the study. **Figure 1** displays the flow of participants. Participant ages ranged from 60 to 94. The majority of participants were male (60%) and Black (68%). Almost half of participants (46%) were single and 40% lived alone.

Outcome

A total of 14/134 (10.4%) of participants met our primary outcome of a fall or all-related injury within 90 days. Only 2/14 (14.3%) of these participants both reported a fall and had a medical record consistent with fall-related injury. <u>Phone follow-ups</u>: A total of 106/136 (79.1%) of enrolled participants provided phone follow-up data at either 1- or 3-months. At 1-month, 5/136 (3.7%) reported a single fall over the past 3-months since enrollment. At 3-months, 6/136 (4.4%) reported a fall since last assessment (at 1-month), only 2 of whom had reported a fall at 1-month follow-up. No baseline characteristics or fall risks were found to be significantly associated with phone-follow-up. <u>Medical record review</u>: Over the 3-months of medical record review, 42/134 (31.3%) of participants had at least one ED re-visit with 9/134 (6.7%) having more than one ED re-visit. A total of 6/42 (14.3%) of these ED re-visits were for fall-related injuries. Over the same period, 20/134 (14.9%) of participants were hospitalized with 3/134 (2.2%) having more than one hospitalization. A total of 3/20 (15.0%) of these hospitalizations were for fall-related injuries.

Predictors

Table 1 provides the baseline characteristics of participants who fell and those who did not. No single characteristic was associated with falls at 3-months. **Table 2** displays the percentage of participants who fell versus did not fall who reported individual risks on the SIQ-12 as well as the univariate assocations between risk and falls. No individual SIQ-12 risk factor was associated with falling. **Table 3** shows the mean differences in each acclerometer feature between participants who had a fall and those who did not. No summary measure of accerometer data was associated with falling.

Models

Table 4 shows operating characteristics of key cutpoints for the SIS-M, the SIQ-12 and the TUG. For the SIS-M, reporting a “moderate problem with mobility” or worse had a positive likelihood ratio [LR+] = 2.86 and a negativelikelihood ratio [LR-] = 0.73. For the SIQ-12, a score of 4 or greater had LR+=1.61 and LR-=0.60. For the TUG, a time to completion of greater than or equal to 26 seconds had a LR+=1.77 and LR-=0.75. **Table 5** displays the performances (i.e. ROC AUCs) of the SIS-M, SIQ-12, TUG and HCRNN models for predicting falls at 3-months. The SIS-M had the worst performance (i.e. BS AUC=0.42; 95% CI 0.19, 0.65) and the HCRNN using generated features had the best (AUC=0.99; 95% CI 0.98, 1.00).

DISCUSSION

Main findings

This study aimed to compare the performance of 4 different fall prediction screening tools for community-dwelling older adults discharged from the ED. We found that none of the traditional fall risk tools validated in other settings had cutoff values that would be good for identifying a subset of older adult ED patients at low risk for future falls. We found that a single question mobility screening question has poor overall model accuracy to distinguish fallers from non-fallers but a self-report of moderate or greater problems with mobility was associated with greater likelihood of falls. We found that the CDC's 12-question fall risk screen had better model accuracy and a score of 4 or greater would identify most older adults who go on to fall after discharge correctly, but no single question was significantly associated with future falls. The overall TUG time did not show good discrimination but a time to completion of more than 26 seconds increased the likelihood of falls after ED discharge. We found, however, that a neural network model using generated features of 3-axis accelerometer data collected during the TUG showed a near-perfect accuracy in discrimination between fallers and non-fallers.

Comparison to other studies

The only existing systematic review of ED-based fall screening tools was published in 2014 by Carpenter et al.[12] In this review, the authors identified only 2 studies examining ED-based screening tools in their predictive ability for future falls for community-dwelling older adults. Our study can be contrasted with these 2 studies in several ways. First, we included patients >= 60 years of age who were not in the ED for a fall. Tiedemann et al.[34] recruited ED patients >= 70 years who were there for a fall and Carpenter et al.[35] recruited ED patients >=65 years who did not present after a fall. They both examined fall outcomes at 6-months post-ED visit, whereas we were interested in short-term (i.e. 3-month) risk. As such, our fall rate was lower (i.e. 10%) compared to Carpenter et al. (i.e. 14%) and Tiedemann et al. (31%). Similar to these studies, we found that no single factor was an accurate predictor of fall risk. Neither of our self-report screening tools (i.e. SIS-M, SIQ-12) were found to be as accurate as the composite score of >1 on a 4-item tool developed by Carpenter, which had predictive LR+ of 2.40 and LR- of 0.11 (95% CI = 0.06 to 0.20). Our self-report screening tools accuracy was similar to those of Harper et al.[36] who reported an ROC AUC=0.57 (95% CI 0.48 to 0.66) for the FROP Com Screen and 0.54 (95% CI 0.45 to 0.63) for their Two-Item Screening Tool.

For the objective functional test (i.e. TUG), Chow et al.[37] found that, among older adults who met high-risk criteria by the CDC's SIQ-12, a TUG test completion time of 12+ seconds had a sensitivity of 70.6% and a specificity of 28.4% to differentiate self-reported fallers from non-fallers at 6-months but an overall poor model ROC AUC of 0.54. Their ROC AUC is similar to the ROC AUC for TUG in our study and the sensitivity and specificity of our TUG time of 22+ seconds. The difference in optimal cutoffs between studies reaffirms prior published concerns about how methodologic differences in how the TUG is conducted can make cross-study comparisons difficult.[38]

There are no prior published reports describing a wearable sensor-based kinematic fall risk screening tool used in the ED. There are however a number of prior systematic reviews of wearable inertial sensors for fall risk assessments in other settings.[39] A review of prospective and retrospective fall prediction studies from 2013 found a wide range of sensitivity (55-100%) and specificity (15-100%) levels for inertial-sensor-based fall risk assessment models.[40] A more recent systematic review including 10 prospective studies testing sensor-based kinematic assessments in other settings found that prediction models achieved sensitivities between 48.1 and 91.3%, specificities between 66.3 and 100.0% and accuracies between 68.0 and 90.0%.[41]

Implications for clinical practice

Predicting future fall risk after an ED visit is important as it allows for the possibility of interventions to reduce harm. In a recent scoping review of 19 studies, Hammounda et al. found that ED-initiated interventions targeting multiple risk factors (e.g. medication review, physical therapy targeting functional limitations, and eliminating environmental hazards) reduce falls among selected older adult ED patients.[42] However, only 2 included ED patients who had not presented to the ED after a fall and 66% entailed fall risk screening, with 11 different tools being used. Our findings can help inform next-generation prognostication models to improve accuracy of identification of older adults who present to the ED for complaints other than a fall, allowing for wider public health impact of targeted fall-prevention interventions.

Strengths and limitations

This study has a number of strengths, including our diverse sample of older ED patients (e.g. 68% Black), our within-sample comparison of multiple screening tools, our novel use of readily-accessible 3-axis accelerometers in smartphones to collect kinematic data, our composite fall outcome of self-report and medical record fall-related care, use of re-sampling procedures (e.g. bootstrapping; leave-one-out) to generate more accurate estimates of prognostic accuracy, and our following of standard guidelines for reporting prognostic tools. There are also a number of limitations to acknowledge. We recruited a convenience sample of ED patients based on RA availability, introducing the possibility of selection bias. We also collected self-reported falls based on retrospective recall at 1- and 3-months follow-up, which may have under-estimated true fall rates due to recall errors. We had a relatively low rate of outcomes per predictor, potentially resulting in over-fitted models. We attempted to minimize over-fitting in the neural network by reducing the predictor pool using generated features only found to be significant in Wald testing. Finally, we did not externally validate our models in new datasets, resulting in likely over-estimation of predictive ability.

CONCLUSION

Consistent with prior ED-based studies, we found evidence that standard screening tools found useful to discriminate older adult fallers form non-fallers in other settings lack sufficient accuracy to be used in isolation in the ED. We did find that a neural network model using generated accelerometer features collected during the TUG in the ED could be a promising modality to improve accuracy of fall prognostication. Further research is needed to externally validate these findings.

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Table 1. Baseline characteristics

Characteristic	Fall (n=14)	No fall (n=120)	OR	95% CI	
Age, mean (SD)	72 (9.8)	68.6 (7.9)	1.05	0.98	1.11
Female	35.7% (5)	40.8% (49)	0.80	0.25	2.55
Race					
White	21.4% (3)	30.0% (36)	REF		
Black	78.6% (11)	68.3% (82)	1.61	0.42	6.11
Other	0	1.7% (2)	NA		
Relationship status					
Married	35.7% (5)	35.8% (43)	REF		
Single	35.7% (5)	48.3% (58)	0.74	0.20	2.72
Separated	0	0.8% (1)	NA		
Widowed	28.6% (4)	15.0% (18)	1.91	0.46	7.94
Living situation					
By self	28.6% (4)	39.2% (47)	REF		
With other >=65	28.6% (4)	17.5% (21)	2.24	0.51	9.82
With other <65	21.4% (3)	28.3% (34)	1.04	0.21	4.94
Multiple family	21.4% (3)	15.0% (18)	1.96	0.40	9.62

Table 2. SIQ-12 risk factors' association with fall outcome

SIQ-12	Fall (n=14)	No fall (n=120)	OR	95% CI	
Any fall in past year	64.3% (9)	42.5% (51)	2.44	0.77	7.70
Worry about falling	35.7% (5)	29.2% (35)	1.34	0.42	4.32
Feel unsteady	50.0% (7)	37.5% (45)	1.67	0.55	5.06
Advised to use ambulation aid	28.6% (4)	10.1% (12)	1.90	0.98	3.64
Needs to hold things	57.1% (8)	24.2% (29)	4.18	1.34	13.10
Have to push self up	50.0% (7)	35.8% (43)	1.79	0.59	5.45
Trouble with curbs	21.4% (3)	25.0% (30)	0.82	0.21	3.13
Rush to go bathroom	71.4% (10)	51.6% (62)	2.34	0.69	7.87
Lose feeling in feet	21.4% (3)	22.5% (27)	0.94	0.24	3.61
Take meds that make lightheaded	42.9% (6)	20.8% (25)	2.85	0.91	8.97
Take meds to modulate mood	42.9% (6)	26.7% (32)	2.06	0.66	6.40
Feels sad or depressed	28.6% (4)	10.0% (12)	3.60	0.98	13.30

Table 3. Accelerometer features' association with fall outcome

Acceleration Signal Amplitude Features	Fall (n=14)	No fall (n=120)	p-value
Mean of ML	-0.38	-0.31	0.73
Mean of AP	9.66	9.65	0.80
Mean of V	1.05	0.91	0.65
Standard Deviation of ML	1.01	1.11	0.21
Standard Deviation of AP	1.27	1.39	0.40
Standard Deviation of V	0.83	1.00	0.04
Pair-wise correlation between ML & AP	0.02	-0.03	0.16
Pair-wise correlation between ML & V	-0.08	-0.03	0.10
Pair-wise correlation between AP & V	0.23	0.18	0.48
Pair-wise covariance between ML & AP	0.01	-0.08	0.31
Pair-wise covariance between ML & V	-0.09	-0.03	0.28
Pair-wise covariance between AP & V	0.33	0.33	0.97
Maximum value of ML	-0.01	-0.04	0.61
Maximum value of AP	0.72	0.70	0.83
Maximum value of V	0.03	0.07	0.51
Maximum difference in ML & AP	0.29	0.26	0.54
Maximum difference in ML & V	0.75	0.76	0.89
Maximum difference in AP & V	0.76	0.77	0.92
Maximum difference in ML & AP & V	0.79	0.80	0.85
HR array for ML	0.81	0.78	0.39
HR array for AP	0.96	0.99	0.88
HR array for V	0.95	0.98	0.76
AP triangle duration for sit to stand	0.42	0.36	0.23
AP triangle duration for stand to sit	0.23	0.22	0.79

Table 4. Model accuracy in discriminating fallers from non-fallers

	AUC	95% CI	
SIS-M	0.63	0.54	0.71
SIS-M (BS)	0.42	0.19	0.65
SIQ-12	0.69	0.60	0.76
SIQ-12 (BS)	0.64	0.49	0.80
TUG	0.60	0.44	0.76
TUG (BS)	0.48	0.29	0.68
HCRNN (raw)	0.98	0.97	0.99
HCRNN (gen)	0.99	0.98	1.00

Table 5. Fall risk estimates for key cutoffs

SIS-M	Sens	Spec	LR+	LR-
>="Slight problem"	50.0	75.8	2.10	0.67
>="Moderate problem"	35.7	87.5	2.86	0.73

SIQ-12	Sens	Spec	LR+	LR-
>=2	100.0	26.7	1.36	0.00
>=3	78.6	41.7	1.35	0.51
>=4	64.3	60.0	1.61	0.60

TUG	Sens	Spec	LR+	LR-
>=18 sec	100.0	8.3	1.09	0.00
>=22 sec	64.3	44.2	1.15	0.81
>=26 sec	42.9	75.8	1.77	0.75

Figure 1. Flow Diagram