Master's Degree Candidate Project

Using Machine Learning to Predict Falls in Loretto Residents

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List of Abbreviations and Key Terms		
EMR = Electronic Medical Record NortonActiv = Norton activity score FA_age = Fall Assessment, age ≥ 85 NortonMencon = Mental condition score	MAR = medication administration record FA_balance = Fall Assessment of balance FA_fallct = Indicates a previous fall RTMS = Real Time Medical Systems	FA_Total = Total Fall Assessment score AgeRange = Nominalized age range FA_mobil = Fall Assessment mobility score

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Abstract

Falls are well known to cause multiple health related complications including death. Despite being surrounded by well trained professionals and an array of preventative devices and equipment, many patients and residents admitted to healthcare facilities in the United States still experience falls and their devastating effects. Healthcare professional have responded to this problem by creating multiple different fall scales and algorithms to predict who will fall so that preventative measures can be deployed to stop falls. Even with such tools in place at healthcare facilities, falls continue to occur. Many of the fall scales and algorithms mentioned were created before the widespread use of electronic medical records (EMRs). The use of modern analytical tools and techniques applied to large datasets in order to better predict falls has yet to be applied in a healthcare institution on a large scale. The purpose of this internship is to analyze health data provided by Loretto to create an algorithm that is able to more accurately predict falls than existing falls scales. A recommendations of SQL queries will be provided to Loretto to be loaded into their RTMS system. This will provide automated daily reports of those residents most likely to fall without increasing the existing workload or changing the workflow of Loretto staff. Preventing falls and their resulting complications will keep residents safer, maintain or improve quality of life and reduce the financial costs associated with falls.

Introduction

There is a significant number of already existing falls risk tools, and previous studies of the effectiveness of these tools. One of the most interesting findings in these articles reported "Widespread use of either MFS [Morse Fall Scale] or STRATIFY is not likely to demonstrate benefits significantly greater than that of nurses' clinical judgement." (Harrington et al, 2010) While interviewing 42 registered nurses with levels of experience ranging from 2 to 41 years, and education ranging from associates to doctorate level working in a medical intensive care unit, 100% reported that the numbers resulting from the fall scale does not impact their level or type of intervention. Instead, the nurses take action based on the patients' level of mobility, agitation, confusion, compliance, visual impairment, and history of falls. These are very similar to items evaluated in most risk tools. These tools were made prior to widespread use of electronic medical records, and as such needed to be easy for a bedside nurse to complete on paper. While creating the John's Hopkins fall risk tool the authors reported "The fact that automated nursing documentation had not been widely deployed in our hospital rendered these scales unacceptable because of burdensome calculation requirements (Morse fall scale) or scale length and complexity (Hendrich II)." (Poe et al, 2004) Furthermore, quality improvement organizations such as HSAG recommend placing a patient on fall precautions if they are any of the following types of medications: anticoagulants, antidepressants, antiepileptics, antihypertensive, antiparkinsonian agents, benzodiazepines, diuretics, nonsteroidal anti-inflammatory agents, psychotropics, vasodilators, laxatives, glycemic medications, tranquilizers, or hypnotics/sedatives (HSAG).

This gives strong support for the use of analytics such as Real Time Medical Systems to be utilized to analyze patients' medical records in a way that humans would be unable to. While medications clearly add to the risk of falls, in cases where medications are still recorded on paper, medical diagnoses might be able to substitute for analysis of medications. For example, if the patient is diagnosed with hypertension, they will most likely be on antihypertensive, if a patient has a history of seizure disorders, they will be on an antiepileptic, and if they have CHF, they might be on diuretics. Analyzing medical diagnoses might be able to show patterns of falls similar to analysis of medications. Utilizing the power of modern computing, the creation of a new fall algorithm should be able to assess the minute details of patients' information and be better able to predict falls.

Mission Statement

Preventing falls and improving residents' quality of life through the meaningful use of health record data and machine learning.

Literature Review

This is a summary of literature reviewed from previously established fall prevention methodologies and how they apply to our creation of a fall prevention algorithm to be used by Loretto. First, to quote a paragraph from Oliver and associates (1997) that exemplifies our current project:

> *"Successful rehabilitation to minimize long term disability of elderly people requires that staff aim to reduce patients' dependency and to increase their autonomy during recovery from acute illness when it is associated with disability. The occurrence of some falls is an unwelcome but probably inevitable consequence of encouraging patients to regain mobility early after acute illness. None the less, there may be simple measures that could reduce the incidence of falls without the need for physical restraints, sedation, excessive supervision, or other measures that undermine a patient's dignity and independence."*

According to the World Health Organization (2017), falls are the second leading cause of accidental injury deaths worldwide. The Centers for Disease Control and Prevention (CDC, 2016) report that "every second of every day in the United States, an older adult falls, making falls the number one cause of injuries and deaths from injury among older Americans." The CDC estimates the annual Medicare cost of falls in older Americans to be $31 billion (CDC, 2016).

Our goal is to create an algorithm that can be used to more positively predict the likelihood of a fall so that appropriate measures can be taken to prevent falls. The best example of the type of algorithm we are looking for is the STRATIFY: St Thomas's Risk Assessment Tool In Falling Elderly Inpatients (Appendix 1) scoring system for assessing fall risk factors (Oliver et al, 1997). STRATIFY assesses 5 patient attributes: fall history, agitation, visual impairment, frequent toileting, and transfer and mobility score. It is not as important to consider what 5 attributes are assessed by STRATIFY because we will be performing historical data analytics on Loretto residents to discover the ideal set of patient attributes to assess for the Loretto algorithm. Reducing the number of assessed attributes to a lower number, such as five with STRATIFY, will make applying an algorithm for Loretto residents more realistic. When creating STRATIFY, they found that "unstable gait" was a powerful estimator of patient falls, but a conscious choice to not include a measure of gait was made to make STRATIFY an easy to execute algorithm. Keeping the number of assessed attributes low can be done without sacrificing the power of the algorithm. When STRATIFY is applied within the patient population in which it was discovered, it could predict that 8 out of 10 patients that scored ≥ 3 (out of 5) did eventually fall (ibid). Reproducing comparable results with fall prevention algorithms in facilities other than the facility the protocol was developed in has historically been a perplexing task. This is a great case for creating a custom algorithm for our Loretto residents that will more precisely predict falls for our specific population.

The Johns Hopkins Fall Risk Assessment Tool (2017) assesses patient age, fall history, frequent toileting, medications, tethered patient care equipment, mobility, and cognition. Johns Hopkins adds weight to the answers for each of these attributes. For example, a fall in the past 6 months or taking two or more high fall risk drugs adds 5 points to the patient's score while being age 60 – 69 years or being tethered to a piece of medical equipment adds 1 point to the patient's score. In contrast, STRATIFY weighs each of their 5 assessed attributes equally. Using data analytics, we may also be able to add weight to each attribute assessed in the Loretto fall prevention algorithm as seen in Figure 2.

Kenny and associates (2001) created a list of common risk factors for predicting fall: 1) muscle weakness, 2) history of falls, 3) gait deficit, 4) balance deficit, 5) use of assistive device, 6) visual deficit, 7) arthritis, 8) impaired activities of daily living (including ambulation and transfer), 9) depression, 10) cognitive impairment, and 11) age > 80 years. Other important risk factors include frequent and assisted toileting, use of "culprit" medications, acute and/or chronic illnesses (including arthritis), and extrinsic factors including bedrail usage, height of seating, and obstacles to ambulation (Oliver et al, 2004; Perell et al, 2001). Gender can sometimes be a factor as was observed by Sherrington and associates (2010).

As we analyze historical data for Loretto residents, we will keep the common risk factors listed above in the back of our minds. We may also discover a significant difference in uncommon factors such as gender. We will approach our analysis with limited bias and allow the computer software to discover the most important patient characteristics to include in our fall prevention algorithm.

A full annotated bibliography is in Appendix 3.

Background

The current fall scale used by Loretto is in their Optimus EMR, and screenshots can be seen in Appendix 4. This scale consists of the following fields: *History of Falls, Vision Status, Cognitive Status/ Behavior Indicators, Continence, Balance, Mobility, Systolic Blood Pressure and Vitals, Age, Health Conditions, and Medications.* These are similar to categories used in the other falls scales previously discussed. The Answers to each section have a certain point value assigned. If the patient scores 9 or more, they are considered to be at risk for falls. All of the patients who have fallen have been at risk as per the falls scale. Therefore, the scale has high sensitivity. However, almost every resident scores positive for being at risk for falls. This means that the scale has low specificity.

With every resident being at risk, the clinical staff is unable to focus fall prevention resources and tactics (seen in Appendix 5). During the shadowing experience with Loretto staff, they echoed the statements by previous nurses above, which were that experience and intuition was utilized to attempt to prevent falls because everyone was at risk for falling according to the scale. What is needed is a more specific scale which could allow staff to focus on the highest 5-10% of residents at risk for falls. Working under the guidance of SUNY Oswego Professor Dr. Isabelle Bichindaritz, and in conjunction with Angela Kiddle and Christine O'Neill from Loretto, we will analyze the date from Loretto's EMR specific to their rehabilitation population, and look for characteristics which correlate with falls more specifically.

Project Timeline

This project consisted of several phases of work. This process was begun following a conference call between Dr. Isabelle Bichindaritz, Angela Kiddle, Christine O'Neill, Joe Miles and Dan Szakielo on June 30th 2017, during which the outline and goals of the project were defined.

First, Joe performed a literature to look at previous research, falls scales and current evidence based practice methods to predict and reduce falls. As a result of this review, and the correlation of certain medications with falls, Joe created a list of "suspect" drugs that may increase fall risk. Dan performed a literature review of experimental and emerging fall prediction/prevention technologies, such as but not limited to wearables.

On October 16th 2017, data from Loretto's EMR was downloaded onto a secure computer disconnected from the network at SUNY Oswego Metro Center. As Loretto has a "hybrid system" that consists of both and EMR and paper, the medication administration record (MAR) is currently on paper. Loretto has plans to add the MAR to the EMR in the future. At this time, it was decided to utilize ICD codes in the analysis because certain medications are used to treat each diagnosis.

Excel, Access, Weka and SPSS modeler were used to perform descriptive analysis on a large patient population including those who have fell and those who have not fallen. The data was predominantly from the residents in the subacute rehabilitation program and would be used to determine fall risk characteristics that can be readily identified from the EMR.

On December 1st 2017 Dan visited Loretto to shadow and observe the nursing staff of the rehabilitation population to get a more complete picture of assessment process and possible challenges and limitations of implementing a new fall prevention algorithm. Loretto staff also discussed risk factors that they intuitively felt were relevant to our specific resident population, and which resident characteristics would be easiest to assess during a normal day. He was also able to see the RTMS dashboard, and examples of current queries that can be run in the system.

This would be helpful in deciding which characteristics would be easier to assess and implement without disturbing current workflows.

On a future date to be determined, the results of this project will be presented to stakeholders at Loretto and we will collaborate to determine feasibility of performing necessary assessments and implementing algorithms. Discussion other technologies and their possible application.

Methods

The raw data from Loretto is in 22 comma-separated value (csv) tables with 11843 resident records from January 2005 to present. Microsoft Access was used to build relationships between the 22 tables (Appendix 7). Sample SQL code used for combining data between the tables can be found in Appendix 8. Linking the resident demographics table to the table of fall incidents helped us to discover that there was at least one fall incident recorded for 1593 residents, or a fall percent of 13.5%. Various tables were created linking multiple patient observations and associating each observation with an end-result of either “Fall” or “NoFall.”

The initial table created put ICD codes into a grid where each record was a different resident and each value was an ICD code specific to that patient. For billing purposes, ICD codes use a decimal format for identifying a specific problem (for example, F03.90 is degenerative, primary, old age, persisting, dementia while F03 would indicate unspecified dementia). To group all patients in a diagnosis, it was decided to remove the decimal specifier and keep only the ICD family. There were 11334 residents that had at least one ICD code. If the resident was also in the fall incident table, then the record indicated that that patient had a “Fall” event. Then, the first ICD code recorded for each of the 11334 residents, along with the binary “Fall”/”NoFall” indicator, was run through an SPSS chi squared analysis and was found to be highly associated with a prediction of fall (Pearson Chi-Square value of 1016.552, 688 degrees of freedom came up highly significant on 2-sided analysis.) The “688 degrees of freedom” translates to 688 different ICD codes evaluated by SPSS. To objectively reduce the number of dimensions in the evaluated table, we uploaded the data into Microsoft Excel to measure the ratio for each ICD code for

"Fall"/"NoFall" (which was a total of 1386 different ICD "families" in the entire table). Because a significant number of the residents didn't fall, it was decided to use a cutoff ratio of 35% or higher "Fall" with at least 24 residents having the ICD code (37 ICD code "families" were identified) or less than 16% incidence of "Fall" with at least 200 residents having the ICD code (32 ICD code "families"). With the list reduced to 69 ICD-families of interest, a new table was created for each resident with 69 variables being each of the ICD-families. If a resident had that ICD in their record, it was recorded as a 1, or recorded 0 if they did not have the ICD.

Using Weka to apply machine learning algorithms to the created tables, it was found that 4 tables were the most promising for creating a reproducible algorithm for predicting fall: ICD, General Admission Observation, Fall Assessment, and Norton (pressure sore risk analysis). Machine learning algorithms used in Weka were Naïve Bayes (NaiveBayes), Logistic Regression (Logistic), k-Nearest Neighbor (IBk), Support Vector Machine (SMO), Neural Network (MultilayerPerceptron), and Decision Trees (J48 and RandomTree). Meta-analysis was also performed with boosting (AdaBoostM1) and stacking (Stacking). Because the data analyzed is mostly nominal or binary, the Decision Tree outperformed all other machine learning algorithms and was used for the remainder of data analysis and algorithm creation.

Characteristics of the 4 tables used for extensive data analysis:

1. ICD: 131911 records (predictive value = 67%)
    a. Transformed to ICD-Grid with 11334 records, 1584 "Fall" (14.0%)
2. General Admission Observation: 52854 records, 15727 "Fall" (29.8%) (predictive value = 62%)
3. Fall Assessment: 26618 records, 8967 "Fall" (33.7%) (predictive value = 68%)
4. Norton: 1305 records (predictive value = 58%)
    a. Transformed table to add "Age On Admission" and "Gender" for each patient.
    b. Resulting table had 1463 records, 431 "Fall" (29.5%) and increased the predictive value to ~75%.

Because most tables were unbalanced (at least 70% "NoFall"), tables were resampled to create a sample set of records with an equal number of "Fall" and "NoFall." Weka has a supervised resample algorithm that was utilized (using a "bias" of 1, sample size percent of 100% with record replacement [oversampled], or a sample size of ≤ 50% with no record replacement [undersampled]).

Feature (variable) reduction was performed in Weka using 3 different attribute ranking algorithms: Chi Square (ChiSquaredAttributeEval), Pearson's correlation coefficient (CorrelationAttributeEval), and Attribute Information Gain (InfoGainAttributeEval). If an attribute appeared near the bottom in 2 of the three ranking evaluators, then the attribute was eliminated from further analysis. As an example of why this is done, a combined table from all four previously mentioned tables, after reducing the total number of variables to 25 still maintained a predictive value of 99.4% (using J48 Decision Tree, result in Table 2), but a Decision Tree model created on test data was only 68.0% accurate on the test data set. This is the phenomenon known as overfitting. With so many records and multiple variables, the machine learning algorithm easily found commonalities with everyone that fell or did not fall. However, when the overly-specific algorithm was applied to previously unseen data, the algorithm did not perform very well.

A training data set was randomly generated with 84786 records and the remaining 21342 were saved in a separate file to be used as test data on each created algorithm. Six algorithms were created and tested (Table 2).

Results

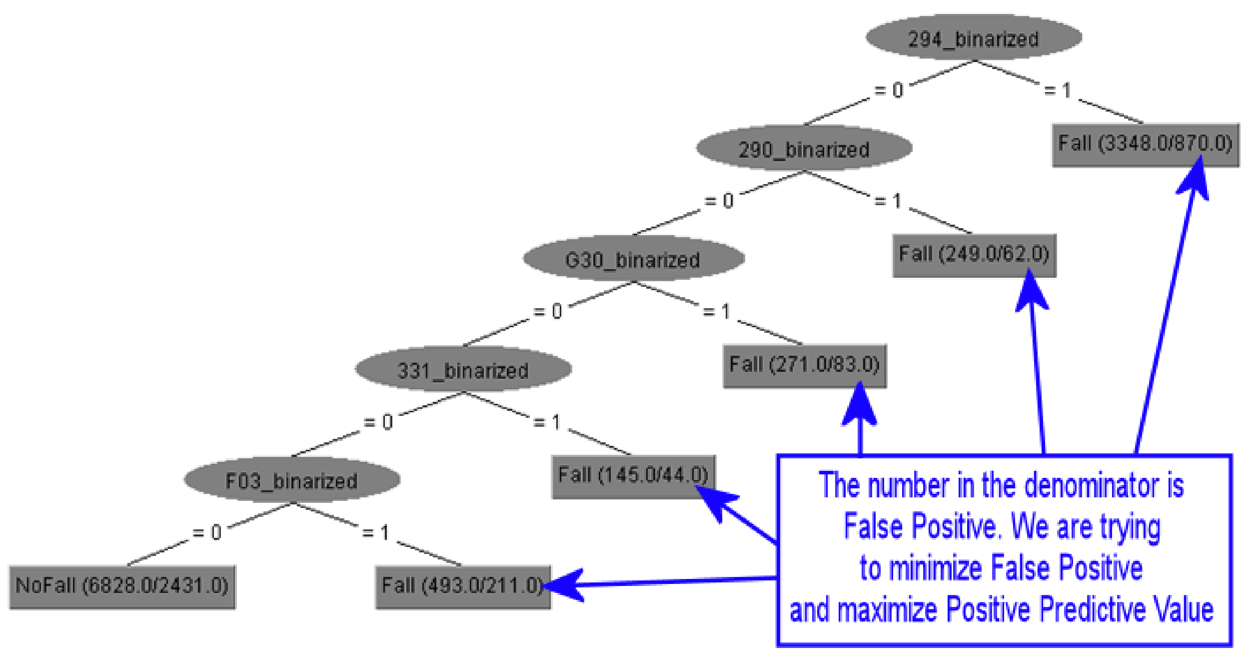
After performing various tests on each of the four tables-of-interest, the number of variables was reduced as seen in Table 1 below. The ICD table was reduced to the following codes: 290 (ICD-9, dementia), 294 (ICD-9, persistent mental disorder), 331 (ICD-9, Alzheimers), F03 (ICD-10, dementia), and G30 (ICD-10, Alzheimers). Weka would not have known that the ICD codes all correlated to some form of mental disorder, so this finding is interesting and consistent with previously known correlations between mental disorder and fall risk. The General Admission Observations table was reduced to measures of: confusion, toilet performance, verbalization of pain, and complaints of chest pain. Fall Assessment was reduced to measures of: previous fall event, behavior and cognitive status (as seen with the observed ICD codes, cognitive status seems significant), age, and general health condition. The Norton table was reduced to measures of: physical condition (similar to measure of "general health condition"), mobility (similar to measure of "toilet performance"), and incontinence. "Age On Admission" and "Gender" had been added to the Norton table and they both were also correlated with an assessment of falling.

Table 1: Feature reduction of each table to a top 18 variable set

ICD	Gen Admission	Fall Assessment	Norton
290	Confusion	Previous fall	Physical condition
294	Toilet Performance	Cognitive status/behavior	Mobility
331	Verbalization of Pain	Age (85 or older)	Incontinence
F03	Complains of chest pain	Health condition	Gender
G30			Age On Admission

An example of a simple decision tree based on the ICD variables in Table 1 is shown in Figure 1.

Figure 1: Decision Tree created for ICD codes



A Decision Tree algorithm was created using the 18 variables listed in Table 1 by using J48 and RandomTree. Results for all tested algorithms can be seen in Table 2.

Table 2: Results of the 6 tested Decision Trees

	J48-18V	RT-18V	J48-25V	J48-8V	RT-8V	RT-Simple
True Pos	4321	6502	6349	7107	6790	6519
False Pos	3197	2701	2854	2647	2194	1666
True Neg	7811	8307	8154	8361	8814	9342
False Neg	6013	3832	3985	3227	3544	3815
Accuracy	56.8%	69.4%	68.0%	72.5%	73.1%	74.3%
Specificity	71.0%	75.5%	74.1%	76.0%	80.1%	84.9%
PPV	57.5%	70.7%	69.0%	72.9%	75.6%	79.6%

J48 = J48 algorithm; RT = RandomTree algorithm; V = number of variables; Simple = Simplified 28-leaf version of the RT-8V algorithm; True Pos = IDed Fallers that Fell; False Pos = IDed Fallers that did not fall; True Neg = IDed non-fallers that did not fall; False Neg = IDed non-fallers that did fall.

The primary goal of this data exploration was to maximize positive predictive value (PPV). By maximizing PPV, we can help the staff at Loretto more precisely identify Fallers that have a high likelihood of "falling" (minimize the false positives that are identified as fallers that will not fall.) With an accuracy of 56.8% and PPV of 57.5% with J48, and an accuracy of 69.4% and PPV of 70.7% with RandomTree, the initial 18-variable dataset did not prove to be helpful. As a comparison, creating a decision tree with only the currently implemented Fall Assessment tool used by Loretto, falls can be predicted with a PPV of 65% and an accuracy of 65.3%.

With the failure of the initial algorithm, the entire dataset of records with all 111 variables was uploaded into Weka. Variable elimination proceeded using the same methods previously discussed. After reducing the number of variables to 25, a 10-fold cross-validation produced 99.428% accuracy as seen on the next page:

Weka: === Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2

Relation: ICDNortonFallGenWekaTrain-weka.filters.unsupervised.attribute.Remove-R1,5,8-9,11,14-16,18-19,21-27,29-49,51-52,54-62,64-67,69-76,78-80,82-89,92-93,95-97,103-111

Instances: 84786

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances 84301 99.428 %
Incorrectly Classified Instances 485 0.572 %
Kappa statistic 0.9884
Mean absolute error 0.0091
Root mean squared error 0.0708
Relative absolute error 1.8592 %
Root relative squared error 14.2789 %
Total Number of Instances 84786
=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.989	0.002	0.998	0.989	0.993	0.988	0.999	0.999	NoFall
	0.998	0.011	0.992	0.998	0.995	0.988	0.999	0.999	Fall
Weighted Avg.	0.994	0.007	0.994	0.994	0.994	0.988	0.999	0.999	

=== Confusion Matrix ===

a	b	<-- classified as
36473	410 |	a = NoFall
75	47828 |	b = Fall

Of particular interest is the 410 false positives while only missing 75 records of fall. Despite the promising results with the training data, as previously mentioned, the algorithm created on this 25-variable training set overfit the training data and did not perform remarkably with the test data (results in Table 2.)

The number of variables were further reduced down to the top 8 variables:

1. Mental Condition from Norton table
2. Activity assessment from Norton table
3. Previous Fall from Fall Assessment table
4. Balance from Fall Assessment table
5. Mobility from Fall Assessment table
6. Age (85 or older) from Fall Assessment table
7. Total score from Fall Assessment table
8. Age Range (derived from patient "Age On Admission" and transformed according to the SQL code in Appendix 8 to nominalize resident age.)

Table 3: Pearson's correlation coefficient and Chi Squared values for the top 8 attributes:

Correlation Coefficient	**Variable name**	**Chi Squared**	**Variable Name**
0.3218	FA_age	12747.04	FA_total
0.3171	NortonActiv	12739	AgeRange
0.2962	NortonMencon	11195.8	FA_mobil
0.2758	FA_fallct	11025.99	NortonActiv
0.2689	FA_balance	10992.9	FA_age
0.1645	AgeRange	9707.791	NortonMencon
0.0581	FA_total	8446.373	FA_balance
0.0267	FA_mobil	8312.388	FA_fallct

FA_Total = Total Fall Assessment score
AgeRange = Nominalized age range
FA_mobil = Fall Assessment mobility score
NortonActiv = Norton activity score
FA_age = Fall Assessment, age ≥ 85
NortonMencon = Mental condition score
FA_balance = Fall Assessment of balance
FA_fallct = Indicates a previous fall

No variables from the General Admission Observation table nor the ICD table were maintained after variable reduction. Three decision trees were created using the training data and the J48 algorithm (with default settings), RandomTree algorithm (with default settings), and a second RandomTree with a limit of 3-levels of decision nodes. Each algorithm performed slightly better than the previously generated model and the simplified 3-level RandomTree performing the best (Table 2, decision tree is in Appendixes 9 and 10). The 79.6% PPV from the test data means that 8 out of 10 residents identified as a potential faller will fall. Despite failing to identify 36.9% of the residents that fell, the maximization of PPV has a greater potential for changing the practice at Loretto as 8 out of 10 identified residents from the currently created model will fall. This stratification of higher-risk fallers could give staff a forewarning that extra preventive measures will need to be taken.

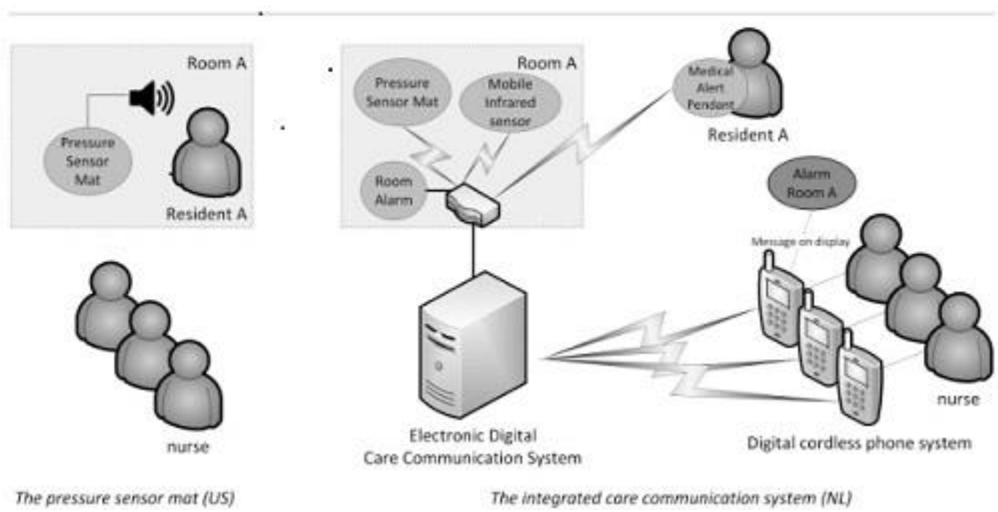
Future Plans

The results of this project are interesting and promising. A literature review of both existing and experimental technologies combined with further work and implementation of the algorithms presented above could provide better predictive capabilities and decreased fall rates. Vandenberg et al. (2017) performed a qualitative study comparing fall prevention technology used in long term care / sub-acute rehabilitation facilities in the United States and Netherlands. They discussed that common devices in the United States included tab and weight-sensitive sensor pad alarms which sounded a loud audible alarm when the patient moved signaling that they might be getting out of bed. Difficulties with these alarms included multiple members of the nursing staff responding to the alarm as they were not sure at first where the alarm was coming from and which resident it was. Furthermore, all nursing staff in the US were considered to be responsible for responding to the alarms. This resulted in other residents being left unattended with incomplete care. Due to the loud noise, residents also felt embarrassed and punished due to the alarm calling attention to them, and caused decreased mobility as residents became afraid to move for fear of setting off the alarm. These findings were echoed on the Loretto visit, as they had recently stopped using chair and bed alarms due to their being considered a restraint as it caused decreased mobility and embarrassment.

The facility in the Netherlands instead used infrared sensors which would detect movement and a resident attempting to get up from bed. Vanderberg et al. (2017) reported that these sensors would only be used on those patients who were considered to be a high risk for falling and who agreed to increased safety precautions versus increased mobility. Instead of an audible alarm going off, a direct message would be sent to a digital cordless phone of the nursing staff primarily responsible for that patient. If the message was unanswered after three minutes, a message would then be sent to another member of the staff. In this way, there was no reason for the resident to feel embarrassed or punished when they were attempting to mobilize, but instead a staff member conveniently appeared to help as they were attempting to ambulate.

As previous literature along with the results mentioned above have shown that those with dementia and other mental illnesses are at increased risk for falling, this population would be less likely to have the ability to contract for safety, and comprehend the possible ramifications of getting up without assistance, a warning device that the patient is about to ambulate could be helpful. Loretto currently uses a pager system where nursing staff primarily responsible for a resident is notified when a patient rings a call bell. It is possible to integrate a pressure sensor device into the call bell system so that a page is sent out that a resident is moving instead of an audible alarm. This would help to achieve the sought-after balance of encouraging mobility while helping to prevent falls. A visualization of both types of movement sensing devices can be seen below in Image 1.

Image 1



Difficulty balancing was another factor prominent in both previous fall scales, as well as the algorithm developed for this project. Tests given at bedside can often be subjective depending on clinician administering the test. Furthermore, testing is often infrequent, with weeks to months in between assessments depending on of the resident is in subacute rehab or long-term care. While utilizing motion detectors and gyroscopes are a possibility, they are cost prohibitive and add greatly to the work of the clinical staff. One possibility for frequent physical therapy and objective monitoring is using a Kinect camera in a video game to improve strength, posture and balance. Schubert et al. (2015) report in their findings of one such study, "Older adults enjoy using the technology and value the feedback provided by the avatar on both their form and progress… These technologies provide an opportunity for prevention with embedded alert systems that are triggered with changes in performance – either a decrease in weekly adherence or an increase in frequency of errors." With such technology in place, regular objective measures could be achieved, and possibly even placed in the EMR. These values could be used to assess if a resident's balance is worsening or improving and if the resident would require more or less resources as a result.

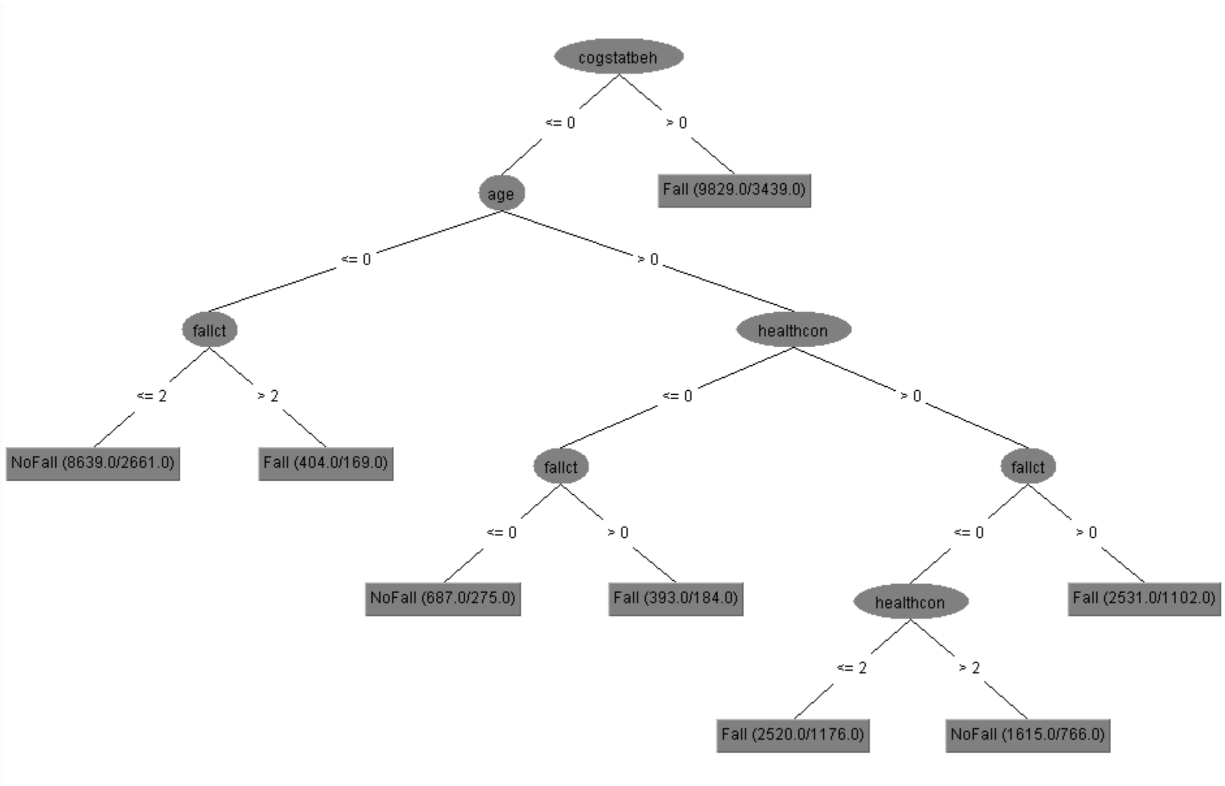
A high risk of falling has been associated with mental disorders in both this project as well as previous studies and fall scales. Medications used to treat such disorders are also associated with high risk for falls (See Appendix 6). The ability to use machine learning to assess the effect of these medications on falls would be invaluable. Whether by having electronic MARs, or obtaining the data through another electronic means would enable a more thorough analysis. If medications were able to be assessed by RTMS, staff would know when a high-risk drug was added or dose adjusted in Realtime, and be better able to assess the patient and their increased risk for fall as a result.

While the assessing for age greater than 85 is in the current MDS fall scale used by Loretto, extra attention should be given to the resident's age. Many of the factors which correlate with a higher risk for fall are also age related. This includes decreased mobility, decreased balance, history of falls, general weakness and mental cognition. Placing a daily query for those residents age 85 and greater would help staff to keep in mind those residents who need extra attention and are at greatest risk for falls. While these are not all inclusive, taking such steps might help to increase vigilance and decrease fall rates.

Discussion

By applying machine learning to the currently used fall assessment at Loretto, we can transform the Loretto fall assessment tool from 36.7% accuracy, 6.8% specificity, and 34.3 PPV, to an algorithm that predicts fall with 63.2% accuracy, 54.7% specificity, and 61.3% PPV. A decision tree created for the fall assessment is pictured in Figure 2. Of note, the following decision tree only uses 4 variables: previous fall (fallct), cognitive status/behavior (cogstatbeh), age (age), and health condition (healthcon).

Figure 2: Fall Assessment Decision Tree result from machine learning



Implementing the above decision tree would positively identify a “faller” 31 out of 50 times versus the current fall assessment that positively identifies a “faller” 17 out of 50 times. Without getting complicated, applying machine learning to fall assessments can meaningfully improve the precision of predicting falls. Statistical sensitivity has not been discussed in this exploratory evaluation because sensitivity was a known sacrifice in order to stratify the highest risk patients. The current fall assessment done by Loretto is 95.7% sensitive, only missing 384 falls out of 8967 incidents. Adding the above decision tree decreased the number of false positives from 16455 to 6030. Using the more specific decision tree pictured in Appendix 10 further decreases the false positives to 1666. Again, false negatives (fallers that are not identified) will also increase. In practice, it can be assumed that no tool will prevent all falls when working in a residential rehabilitation setting that encourages residents to become more independent during their stay. Using data analytics to identify residents at the highest risk of falling could become an important aspect of preventing falls in the future.

The code necessary to apply the model in Figure 2 would be as simple as adding the following SQL to the daily RTMS run:

```
SELECT resident_id,
        CASE
          WHEN cogstatbeh > 0 THEN ‘Fall’
          WHEN age = 0 AND fallct <= 2 THEN ‘NoFall’
          WHEN age = 0 AND fallct > 2 THEN ‘Fall’
          WHEN healthcon = 0 AND fallct = 0 THEN ‘NoFall’
          WHEN healthcon = 0 AND fallct > 0 THEN ‘Fall’
          WHEN fallct = 0 AND healthcon <= 2 THEN ‘Fall’     -- this is counterintuitive, at this branch
          WHEN fallct = 0 AND healthcon > 2 THEN ‘NoFall’  -- poorer “health condition” = ‘NoFall’
          ELSE ‘Fall’
        END AS DecisionTreeFallAssessment
   FROM Falls_risk
   WHERE DischargeDate IS NULL  -- this line would need to be fixed to point at a real “DischargeDate” field
   ORDER BY resident_id;
```

It is important to note that the findings of this data analysis are particular to the residents in Loretto. To create a useful algorithm for other facilities, machine learning should be applied to that facility’s data to create a decision-model specific to that population. The procedures used in this evaluation need to be validated through re-test, ideally through prospective application of the established decision algorithm with current and future residents in Loretto’s rehabilitation unit.

This was an exploratory evaluation of applying machine learning to data from an electronic medical record. Future studies will need to be developed to test the theories brought up during this evaluation. Adding more data, such as medication usage, or adding automated data from a patient wearable could also be studied for incorporation into a machine learning algorithm for precisely preventing fall.

There are several limitations of this current evaluation that need further exploration. First, the process of table creation involved combining several records for each resident from five different tables. The fifth table, not previously mentioned, was the admission/discharge/transfer table to establish the resident's age on admission(s). Many patients had several admissions causing some patients to be evaluated multiple times. The positive of this effect is that patients that fell in one admission did not necessarily fall in all admissions, so they would have acted as their own control if this were a scientific study. The problem occurs when the other four tables are combined. Since residents may have multiple assessments performed during each stay, that one admission will become duplicated exponentially with each table added. As an example of the phenomenon being described, the Norton table, with only 1305 records, was the last table to be added. When matched with all of the records matching that resident's visit, the resultant table had 106128 records meaning that each Norton record may have been duplicated approximately 81 times. The resultant resampled records produced a test and train dataset with approximately equal numbers of fall events versus non-fall visits. In terms of applying the findings of this evaluation to future study, the additional decision tree provided in Figure 2 should be equally considered to the decision tree in Appendix 10 because the former tree would not have had the duplicate records to affect the weighting of the decisions made by the machine learning algorithm of the latter tree. Another limitation in the data analysis is that each stay a resident had was correlated with a binary "Fall"/"NoFall." The practical problem with this method is that a patient assessment may have been performed after a fall incident. Since previous fall has a strong correlation with potential future fall events, any evaluation performed after a resident has already fallen will probably be biased. Some residents in the dataset had a length of stay in the hundreds, or even thousands of days, so there may be some confounding data from patients that were not typical residents of a rehabilitation residence. A resident with a long length of stay will also have more assessments giving that resident a higher weight in the data analysis. To carry the ideas from this evaluation to a prospective study, there would need to be a system for prospective analysis as well as a more complete list of resident demographics to control for factors like race, ethnicity, education, and socio-economic status.

Acknowledgments

We would like to thank Dr. Isabelle Bichindaritz for advising us and leading us through both the planning and implantation stages of this project. Discussing the project each week with her gave us special insight into solving complex problems. Special thanks are also due to Christine O'Neill and Angela Kiddle who were patient with all questions, and more than helpful in taking time out of their busy schedules in order to meet with us, and explain Loretto's processes, and fall prevention strategies. Alicia RN was also very cooperative and helpful, making the shadowing experience a worthwhile learning opportunity. The BHI program at SUNY Oswego, has greatly helped to prepare us with a proper mix of education and experience with which we can feel confident entering the world of Biomedical Informatics and Health Information Technology.

Educational Statement

This internship was an excellent educational opportunity which helped to test a variety of skills and knowledge we have gained so far. Working knowledge of SQL and the ability to write queries proved invaluable and were used often in order to manipulate the large amount of data and create tables to analyze in Weka. We learned the importance of preprocessing and cleaning the data before we were able to analyze it. This by far was the most labor intensive and time-consuming part of the project.

Using SPSS and Weka were new experiences for both of us, and both proved to be truly powerful tools in the analysis of the large data sets from Loretto. Predictive analytics holds such great promise in the world of big data analytics. The ability to get a more specific falls algorithm through this analysis was a great experience.

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Appendix 1: STRATIFY Risk Assessment Tool

STRATIFY Risk Assessment Tool

Answer all five questions below and count the number of "Yes" answers.

#	Question	Yes / No	
1	Did the patient present to hospital with a fall or has he or she fallen on the ward since admission (**recent history of fall**)?	Yes = 1	No = 0
2	Is the patient **agitated**?	Yes = 1	No = 0
3	Is the patient **visually impaired** to the extent that everyday function is affected?	Yes = 1	No = 0
4	Is the patient in need of especially **frequent toileting**?	Yes = 1	No = 0
5	Does the patient have a combined **transfer and mobility** score of 3 or 4? (calculate below)	Yes = 1	No = 0
	Transfer score: Choose **one** of the following options which best describes the patient's level of capability when transferring from a bed to a chair: 0 = Unable 1 = Needs major help 2 = Needs minor help 3 = Independent		
	Mobility score: Choose **one** of the following options which best describes the patient's level of mobility: 0 = Immobile 1 = Independent with the aid of a wheelchair 2 = Uses walking aid or help of one person 3 = Independent		
	Combined score (**transfer + mobility**): ___________		
	Total score from questions 1-5: ___________ 0 = Low risk 1 = Moderate risk **2 or above = High risk**		

This assessment is an example of what we are trying to create, substituting factors that are specific to Loretto residents to stratify fall risk and prospectively prevent falls.

Appendix 2: **Johns Hopkins Risk Assessment Tool**

Johns Hopkins
Fall Risk Assessment Tool

If patient has any of the following conditions, check the box and apply Fall Risk interventions as indicated.

High Fall Risk - Implement High Fall Risk interventions per protocol

- ☐ History of more than one fall within 6 months before admission
- ☐ Patient has experienced a fall during this hospitalization
- ☐ Patient is deemed high fall-risk per protocol (e.g., seizure precautions)

Low Fall Risk - Implement Low Fall Risk interventions per protocol

- ☐ Complete paralysis or completely immobilized

Do not continue with Fall Risk Score Calculation if any of the above conditions are checked.

FALL RISK SCORE CALCULATION – Select the appropriate option in each category. Add all points to calculate Fall Risk Score. (If no option is selected, score for category is 0)	**Points**
Age *(single-select)* ☐ 60 - 69 years (1 point) ☐ 70 -79 years (2 points) ☐ greater than or equal to 80 years (3 points)	
Fall History *(single-select)* ☐ One fall within 6 months before admission (5 points)	
Elimination, Bowel and Urine *(single-select)* ☐ Incontinence (2 points) ☐ Urgency or frequency (2 points) ☐ Urgency/frequency and incontinence (4 points)	
Medications: Includes PCA/opiates, anticonvulsants, anti-hypertensives, diuretics, hypnotics, laxatives, sedatives, and psychotropics *(single-select)* ☐ On 1 high fall risk drug (3 points) ☐ On 2 or more high fall risk drugs (5 points) ☐ Sedated procedure within past 24 hours (7 points)	
Patient Care Equipment: Any equipment that tethers patient (e.g., IV infusion, chest tube, indwelling catheter, SCDs, etc.) *(single-select)* ☐ One present (1 point) ☐ Two present (2 points) ☐ 3 or more present (3 points)	
Mobility *(multi-select; choose all that apply and add points together)* ☐ Requires assistance or supervision for mobility, transfer, or ambulation (2 points) ☐ Unsteady gait (2 points) ☐ Visual or auditory impairment affecting mobility (2 points)	
Cognition *(multi-select; choose all that apply and add points together)* ☐ Altered awareness of immediate physical environment (1 point) ☐ Impulsive (2 points) ☐ Lack of understanding of one's physical and cognitive limitations (4 points)	
Total Fall Risk Score (Sum of all points per category)	
SCORING: 6-13 Total Points = Moderate Fall Risk, >13 Total Points = High Fall Risk	

JOHNS HOPKINS MEDICINE

Appendix 3: Annotated Bibliography

Haines, TP; Bennell, KL; Osborne, RH; Hill, KD. (2004). Effectiveness of targeted falls prevention programme in subacute hospital setting: randomised controlled trial. *British Medical Journal*. 328(7441): 676. doi: 10.1136/bmj.328.7441.676

"Stroke rehabilitation units have reported up to 47% incidence of falls." To address fall risk in rehabilitation, they created the Peter James Centre Falls Risk Assessment Tool (PJC-FRAT). The assessment tool evaluates the "Medical" assessment of: frequent unexplained falls, having a medical condition that causes increased fall risk, and medication usage. "Nursing" assessment includes: Toileting (day and night). "Physiotherapy" assessment of gait and transfers. "Occupational Therapy" assessment of bathing and dressing. Also, there is an "All Disciplines" assessment of patient noncompliance, especially with the use of aids and supervision of activities. By their measure, this multidisciplinary assessment resulted in a 30% decrease in falls. Though the fall prevention is noteworthy and the patient population matches our Loretto patient population, results are not conducive to an objective measure of fall risk based on recorded patient data in an electronic medical record.

Haines TP; Bennell KL; Osborne RH; Hill KD. (2006). A new instrument for targeting falls prevention interventions was accurate and clinically applicable in a hospital setting. *Journal of Clinical Epidemiology*. 59: 168–175. doi: 10.1016/j.jclinepi.2005.07.017

Validation of a fall risk assessment tool, Peter James Centre Falls Risk Assessment Tool (PJC-FRAT), requiring "multidisciplinary input to identify several falls risk factors." Results were compared to STRATIFY in phase 1 of the study. The study confirms the cutoff of STRATIFY to ideally be 2 or higher for fall prediction. The patient population is from a rehabilitation facility. Some of the focus of this article is on implementing preventative measures such as "Fall Risk Alert Cards" (to be placed near a resident's bed to signify that the resident is at an increased fall risk using symbols rather than words to maintain patient confidentiality) along with other treatment strategies such as exercise, education and hip padding (hip protectors.) The PJC-FRAT uses professional judgement from practitioners and would not be very useful in establishing an objective measure of fall risk.

Johns Hopkins Fall Risk Assessment Tool**. Retrieved 9/13/2017 from http://www.hopkinsmedicine.org/institute_nursing/models_tools/JHFRAT_acute%20care%20original_6_22_17.pdf**

Much like STRATIFY, there is an emphasis on assessing patients that are medium mobility risk (on STRATIFY, those with transfer and mobility score of 3 or 4 out of six). If someone is completely immobilized, they are obviously not a fall risk. And, if someone has a history of more than one fall within the past 6 months, has fallen in the facility, or is deemed high fall-risk due to a diagnosis (such as seizure precaution), then fall prevention measures need to be in place regardless of any other assessment. The John Hopkins' assessment quantifies/stratifies its measures: 60-69 years old = 1 point, 70-79 = 2 points and over 80 = 3 points. One fall in past 6 months = 5 points. Incontinence is 2 points, urgency and frequency is also 2 points and the combination of both is 4 points. Medications of interest are noted as opiates, anticonvulsants, anti-hypertensives, diuretics, hypnotics, laxatives, sedatives, and psychotropics are given a score of 3 for one in list, 5 for two or more, or 7 points if patient had a sedated procedure within the past 24 hours. Equipment of interest includes IV infusion, chest tube, indwelling catheter, sequential compression device, etc and is given a score of 1 for one, 2 for two, and 3 for three devices. For mobility, requires assistance = 2 points, unsteady gait = 2 points, and visual or auditory impairment = 2 points. Finally, cognition: altered awareness = 1 point, impulsive = 2 points, and "lack of understanding of one's physical and cognitive limitations" = 4 points. "High Fall Risk" is anyone that scores over 13 points.

The above is simply a written-out list of the form, but this exercise, though redundant, is important for establishing important patient parameters to assess. With a multitude of patient data, it is important that we feature select the most relevant data.

Kenny, RA; Rubenstein, LZ; Martin, FC; Tinetti, ME. (2001). Guideline for the Prevention of Falls in Older Persons. *Journal of the American Geriatrics Society*. 49(5): 664-672.

From analyzing 16 studies assessing risk fall predictive factors, the list of most common risk factors in order of predictive power includes: 1) muscle weakness, 2) history of falls, 3) gait deficit, 4) balance deficit, 5) use of assistive device, 6) visual deficit, 7) arthritis, 8) impaired activities of daily living, 9) depression, 10) cognitive impairment, and 11) age > 80 years. Interventions noted in this study are exercise (can we assume strength of patient from an EMR?), environmental modifications (is something physically causing residents to fall?), medication usage (notably, anyone taking four or more medications or anyone taking psychotropic medications), cardiovascular intervention (syncope from medication side-effects or untreated cardiac condition), and visual intervention (assess vision difficulty).

Nyström, A; Hellström, K. (2013). Fall risk six weeks from onset of stroke and the ability of the Prediction of Falls in Rehabilitation Settings Tool and motor function to predict falls. *Clinical Rehabilitation*. 27(5): 473-479. doi:10.1177/0269215512464703

Patient population is stroke victim rehabilitation residents. Study assesses the value of a fall prevention tool called Predict-FIRST (Falls in Rehabilitation Settings Tool). See Sherrington et al (2010) for more about Predict-FIRST. Mostly, this study confirms the assessment I made from Sherrington et al, but this study was under-powered with having an n=68. Only 7 of the residents (10% of the total population) scored a 4 out of 5 on Predict-FIRST (and no resident scored a 5 out of 5), and 6 of those residents had a falling event (86%). That result would be ideal for our project, but I am suspicious that the underlying comorbidity of having had a recent stroke and the low power of the study makes the result of this study questionable. Again, refer to Sherrington et al (2010) for more information concerning Predict-FIRST (especially my questioning of using gender as 1 of the 5 risk factors assessed, giving "male" gender 20% weight on this scale and potentially under-weighting the score for women at risk of fall.)

Oliver, D; Britton, M; Seed, P; Martin, FC; Hopper, AH. (1997). Development and evaluation of evidence based risk assessment tool (STRATIFY) to predict which elderly inpatients will fall: case-control and cohort studies. *British Medical Journal*. 315: 1049-1053.

This is a review and follow up by some of the same individuals that developed the STRATIFY risk assessment tool. This study is from the perspective of hospital care. Common significant fall risk factors identified include (in no particular order): 1) gait instability, 2) lower limb weakness, 3) agitation/confusion, 4) urinary incontinence/frequency (or need for assisted toileting), 4) falls history, 5) culprit drugs (especially sedative/hypnotics). The positive predictive value (number of falls in patients that screen as high risk / number of all patients that screen as high risk) of the STRATIFY test was much higher than the other 6 screening tools assessed. These results are more significant when you increase the minimum score for high risk in the STRATIFY test (for example, positive predictive value of a STRATIFY score ≥ 2 is 62% and ≥ 3 is 80%). The take home for Loretto is that we can create a risk assessment tool similar in form and function to the STRATIFY tool by substituting fall risk factors specific to Loretto residents. We can raise or lower the minimum value necessary to stratify high risk residents to ensure that we are maximizing resources towards preventing falls in our highest risk residents.

For more details about STRATIFY, see the below.

Oliver, D; Daly, F; Martin, FC; McMurdo, MET. (2004). Risk factors and risk assessment tools for falls in hospital in-patients: a systematic review. *Age and Ageing*. 33(2): 122-130. doi:10.1093/ageing/afh017

First, to quote a paragraph in the introduction that exemplifies our current project:

> *"Successful rehabilitation to minimise long term disability of elderly people requires that staff aim to reduce patients' dependency and to increase their autonomy during recovery from acute illness when it is associated with disability. The occurrence of some falls is an unwelcome but probably inevitable consequence of encouraging patients to regain mobility early after acute illness. None the less, there may be simple measures that could reduce the incidence of falls without the need for physical restraints, sedation, excessive supervision, or other measures that undermine a patient's dignity and independence."*

This study defines the STRATIFY (St Thomas's Risk Assessment Tool In Falling Elderly Inpatients) unweighted scoring system for assessing fall risk factors. The basis of STRATIFY is that previous studies had shown that assessing a few risk factors may predict a sizable percentage of falls. Of note, not really mentioned in this study but validated by the study's result, studies have shown that there may be a regional aspect to the risk factors that may be ideal for predicting falls as well as differences in the underlying patient population.

Tranfer score: 0 = unable, 1 = major help needed (physically aided), 2 = minor help (verbal or physical), 3 = independent.

Mobility score: 0 = immobile, 1 = independent with aid of wheelchair, 2 = walks with help of one person, 3 = independent.

Adding transfer score to mobility score creates a scale of 0-6. 46% of fallers had a score of 3 or 4. The 5 factors (binary 'yes' = 1 or 'no' = 0) chosen for the STRATIFY tool were: fall history, agitation, visually impaired to the extent that everyday function is affected, frequent toileting, and transfer+mobility score of 3 or 4 (see Appendix). The study also found significant correlation of falls with unstable gait and the presence of antiarrhythmic drugs (not with any other drugs), but they chose not to use these in their assessment tool. Interesting result is that the positive predictive value of a STRATIFY test score of 3 or higher validated in a local population had a positive predictive value of 80.3% (Falls in score ≥ 3 / All score ≥ 3). Only 12 of 324 people in the validation arm of the study had a score ≥ 3 and did not fall while 49 people with the same scores did fall. These are the type of results we are hoping to duplicate in Loretto: high predictive value so we are not wasting staff resources on people that would not fall regardless of intervention. Also interesting, in a second validation in a remote location, the assessment results were not as significant. 43 of 363 people fell with a score ≥ 3, but 36 people fell with a score < 3 and 45 people did not fall with a score ≥ 3. What makes this result applicable to the current project is the importance of choosing factors to assess that are specific to the Loretto population, not necessarily something that worked somewhere else. Many human factors can factor into this discrepancy of results in different locations, but it is significant to emphasize that our results should be reflective of Loretto resedints.

Perell, KL; Nelson, A; Goldman, RL; Luther, SL; Prieto-Lewis, N; Rubenstein, LZ. (2001). Fall Risk Assessment Measures: An Analytic Review. *Journal of Gerontology: Medical Sciences*. 56A(12): M761-M766.

Sobering quote to keep our "eyes on the prize" of fall prevention: "Injury due to falls is the leading cause of death in older adults." This review is over 16 years old, so that quote would need to be reevaluated, but it is safe to say that falls are a major cause of mortality as well as morbidity. They also postulate that postfall anxiety / fear of falling occurs in 73% of patients that have previous fallen and this anxiety inhibits independence and negates gains made through rehabilitation. Fall risk factors identified in this study include: 1) cognitive impairment/psychological status, 2) acute/chronic illness (arthritis), 3) sensory deficits (seeing, hearing), 4) fall history, 5) elimination, 6) muscle weakness, 7) gait/balance deficits and use of assistive devices, 8) age > 80 years, 9) impaired activities of daily living, and 10) culprit medications or polypharmacy. Extrinsic/environmental factors include: 1) use of bedrails, 2) height and stability of seating, 3) obstacles created by mobility aids (wheelchair/walker), and 4) the process of ambulation/transfer in bathroom. The authors seem to be skeptical of using an off-the-shelf assessment tool in residential care settings. This conclusion is conducive with our current program since we are planning on discovering our own risk factor set.

Saverino, A; Waller, D; Rantell, K; Parry, R; Moriarty, A; Playford, ED. (2016). The Role of Cognitive Factors in Predicting Balance and Fall Risk in a Neuro-Rehabilitation Setting. *Plos ONE*. 11(4): 1-14. doi:10.1371/journal.pone.0153469

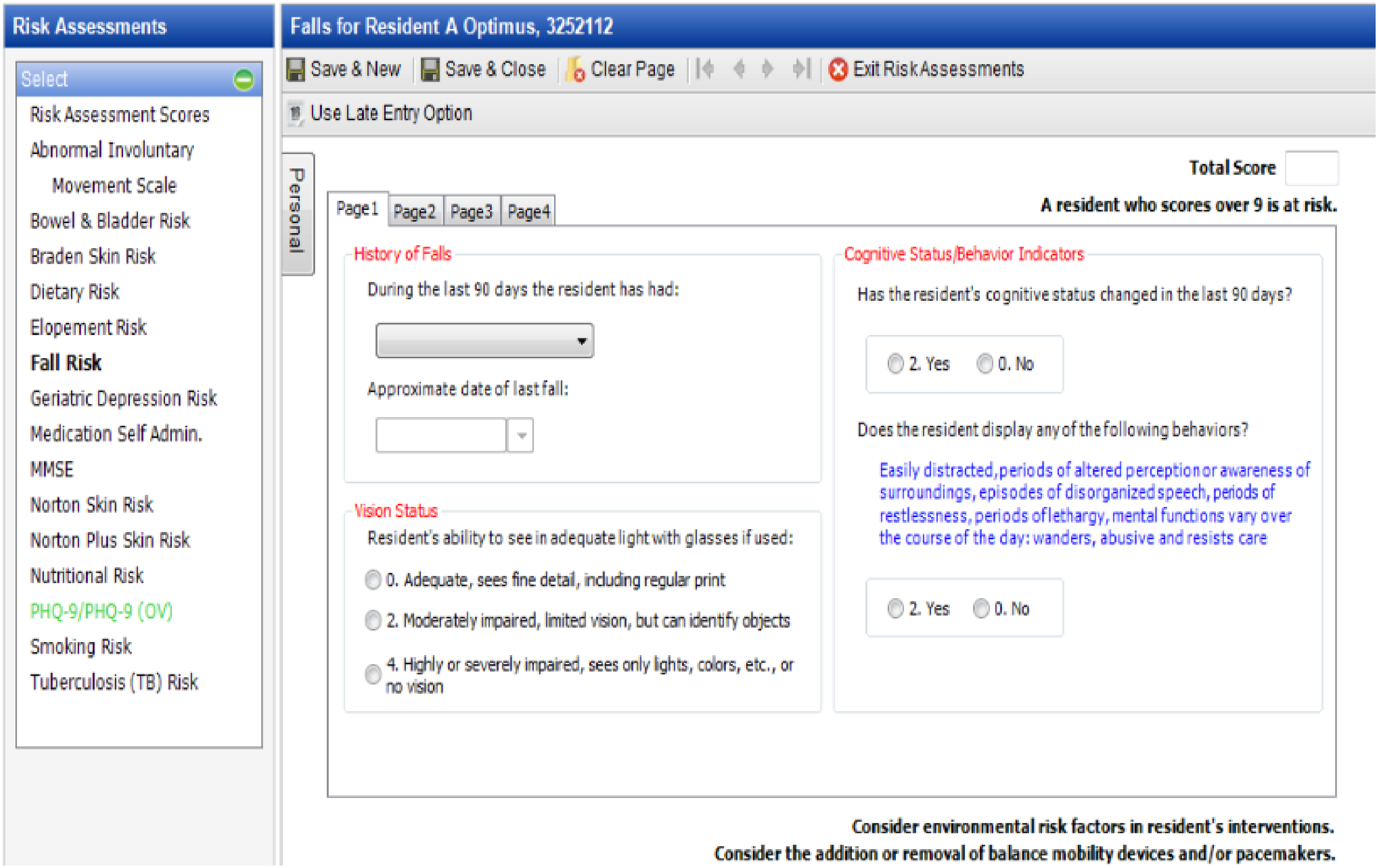
This study specifically assesses the correlation between cognitive factors and fall risk. Excellent information processing speed and visual memory highly correlate with better balance. Test results that showed a correlation with falls included poor results from the Stroop Color Word Test (measures selective attention to colors of writing versus color words such as red and blue, the cognitive flexibility to complete the task and the speed with which the task is completed) and the Trail Making Test: Part B (attention, speed, cognitive flexibility, and visual-motor coordination.) Results of this study are not overly significant for our project other than to recognize the significance of cognition, especially cognitive speed, attention, and flexibility to change focus. Adding these details as a measure would be highly difficult. However, a global assessment of cognitive impairment based on factors in the electronic medical record continues to hold potential for our prospective assessment of Loretto residents.

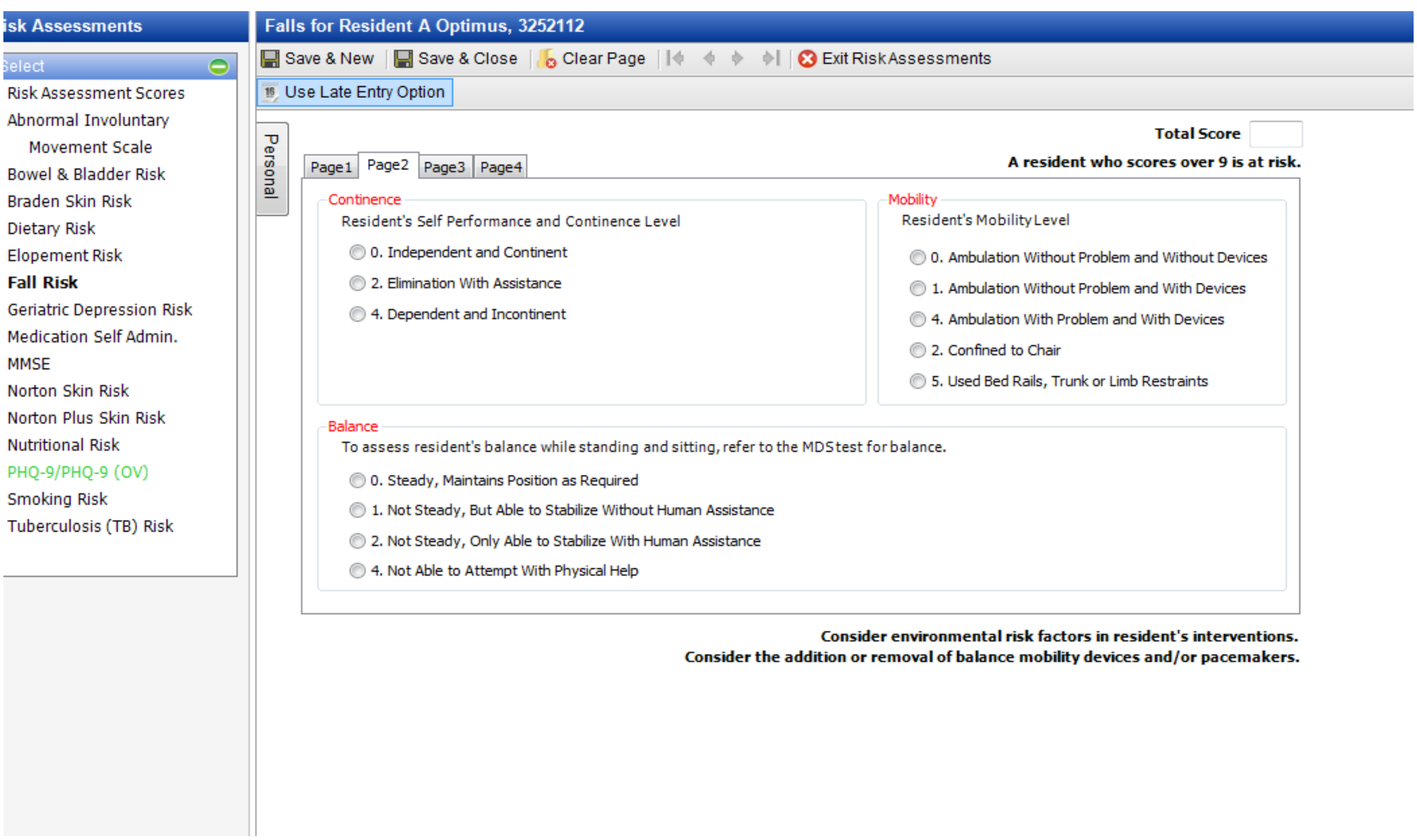
Quote: "It has been suggested that gait and balance can no longer be considered simple motor activities but rather complex and goal-oriented activities requiring constant awareness of body movements and the surrounding environment."

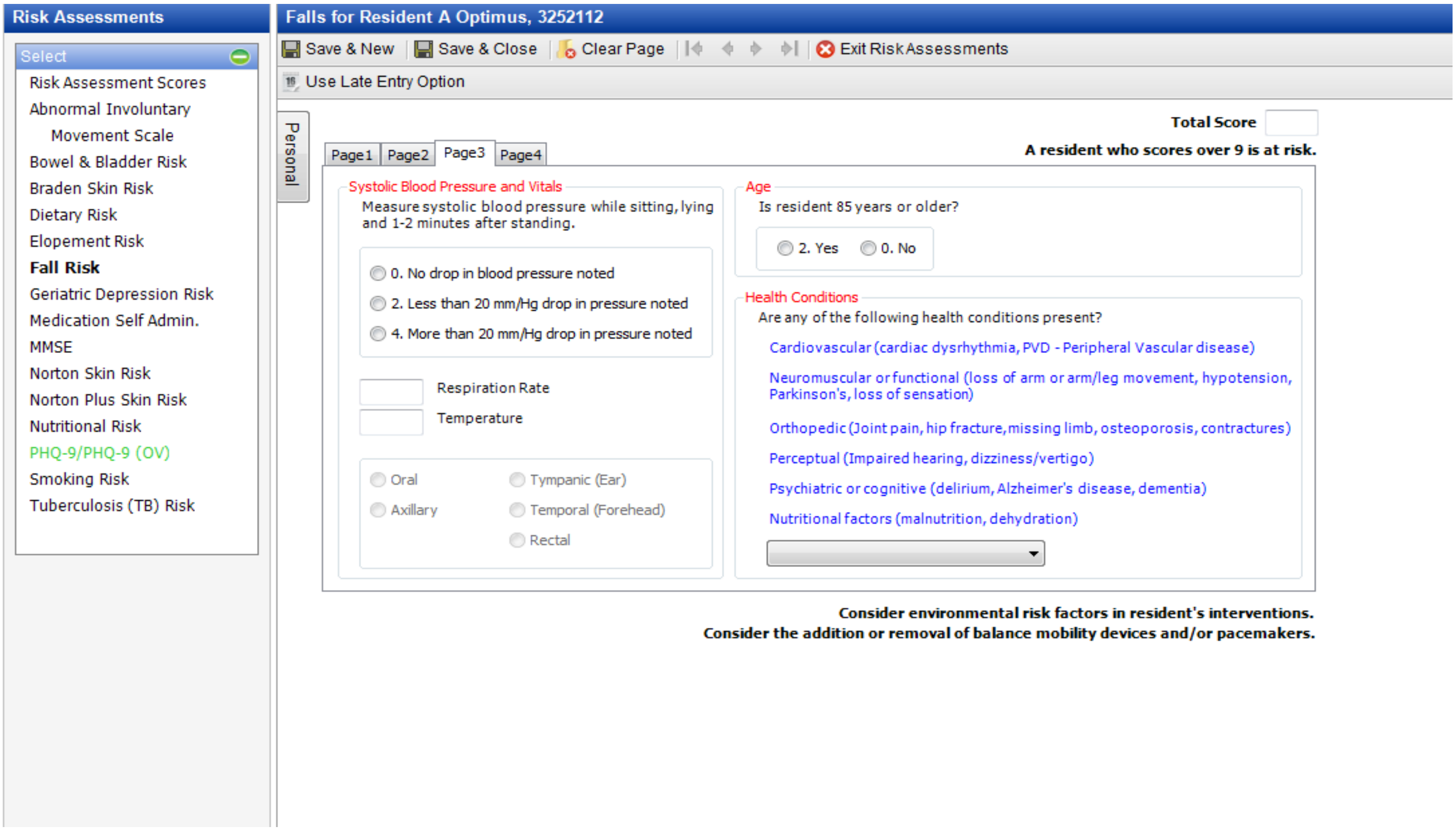
Sherrington, C; Lord, S; Close, JCT; Barraclough, E; Taylor, M; O' Rourke, S; Kurrle, S; Tiedemann, A; Cumming, RG; Herbert, R. (2010). Development of a tool for prediction of falls in rehabilitation settings (Predict FIRST): a prospective cohort study. *Journal Of Rehabilitation Medicine.* 42: 482-488. doi:10.2340/16501977-0550

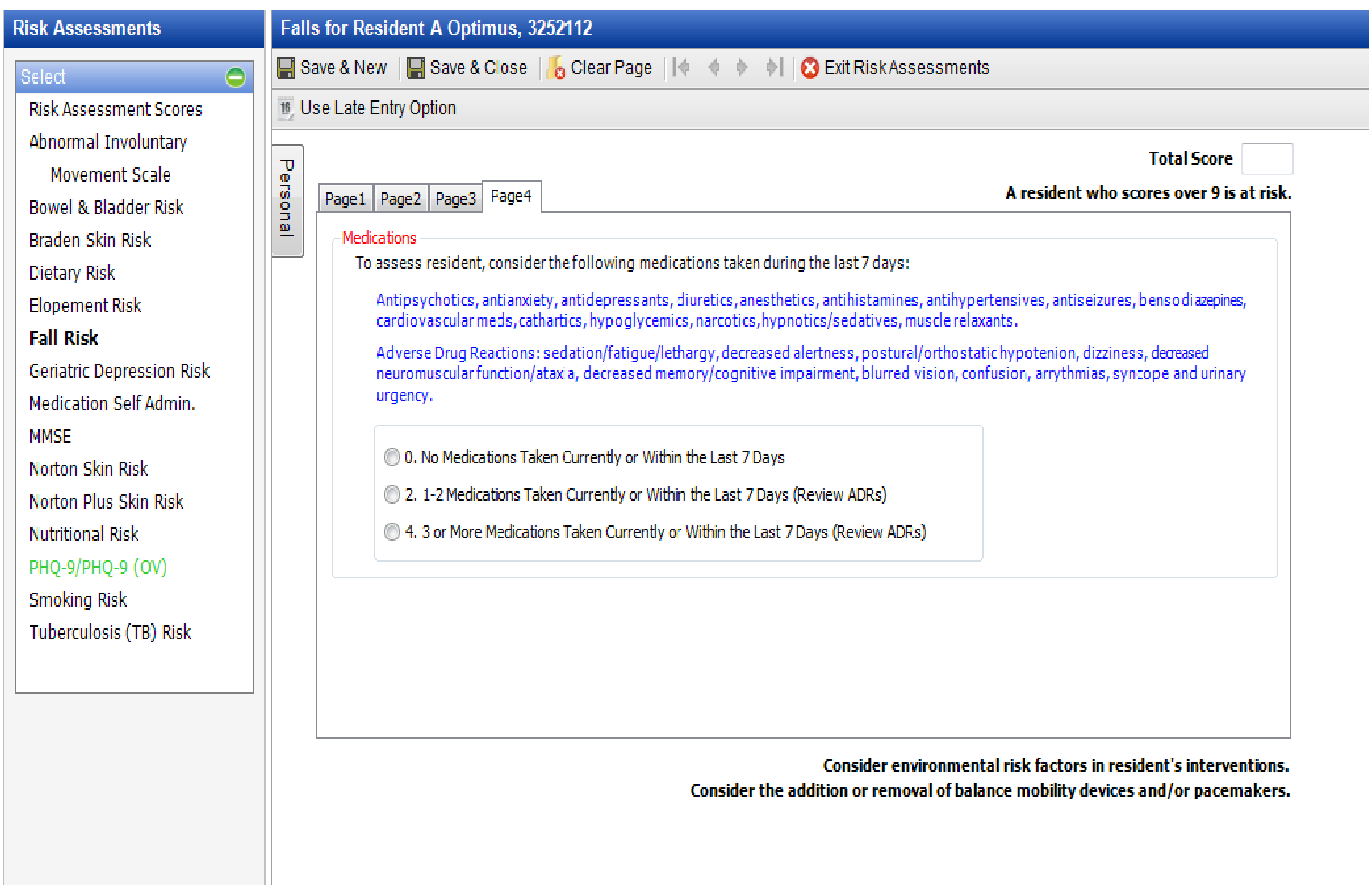
Development of Predict-FIRST (Prediction of Falls In Rehabilitation Settings Tool). Predict-FIRST assesses 5 risk factors. Interesting excerpts from the study: a 5 out of 5 "would be a **man,** prescribed **CNS medications**, who needed **frequent visits to the toilet**, had **fallen in the last year,** and **could not perform a tandem stand**. Based on the outcome of this study, having fewer than 3 of the bolded traits relates to approximately a 6% probability of fall. Scoring 3 or higher equates to a 25% probability of fall, but encompassed 44% of the studied population (234 of 533 tested residents). Having a 4 or 5 encompassed 16% of the population (85 subjects) and equated to a 32% probability of falling. With gender (male) as one of the 5 characteristics, it seems that women may be underweighted on this scale, especially if using 4 out of 5 as a cutoff. For our usage, a test that would only eliminate 56% of evaluated residents.

Appendix 4: Loretto Fall Risk Assessment Tool






Risk Assessments
Select
Risk Assessment Scores
Abnormal Involuntary Movement Scale
Bowel & Bladder Risk
Braden Skin Risk
Dietary Risk
Elopement Risk
Fall Risk
Geriatric Depression Risk
Medication Self Admin.
MMSE
Norton Skin Risk
Norton Plus Skin Risk
Nutritional Risk
PHQ-9/PHQ-9 (OV)
Smoking Risk
Tuberculosis (TB) Risk
Falls for Resident A Optimus, 3252112
Save & New
Save & Close
Clear Page
Exit Risk Assessments
Use Late Entry Option
Personal
Total Score
A resident who scores over 9 is at risk.
Page1 Page2 Page3 Page4
Systolic Blood Pressure and Vitals
Measure systolic blood pressure while sitting, lying and 1-2 minutes after standing.
0. No drop in blood pressure noted
2. Less than 20 mm/Hg drop in pressure noted
4. More than 20 mm/Hg drop in pressure noted
Respiration Rate
Temperature
Oral
Tympanic (Ear)
Axillary
Temporal (Forehead)
Rectal
Age
Is resident 85 years or older?
2. Yes
0. No
Health Conditions
Are any of the following health conditions present?
Cardiovascular (cardiac dysrhythmia, PVD - Peripheral Vascular disease)
Neuromuscular or functional (loss of arm or arm/leg movement, hypotension, Parkinson's, loss of sensation)
Orthopedic (Joint pain, hip fracture, missing limb, osteoporosis, contractures)
Perceptual (Impaired hearing, dizziness/vertigo)
Psychiatric or cognitive (delirium, Alzheimer's disease, dementia)
Nutritional factors (malnutrition, dehydration)
Consider environmental risk factors in resident's interventions.
Consider the addition or removal of balance mobility devices and/or pacemakers.


Risk Assessments
Select
Risk Assessment Scores
Abnormal Involuntary Movement Scale
Bowel & Bladder Risk
Braden Skin Risk
Dietary Risk
Elopement Risk
Fall Risk
Geriatric Depression Risk
Medication Self Admin.
MMSE
Norton Skin Risk
Norton Plus Skin Risk
Nutritional Risk
PHQ-9/PHQ-9 (OV)
Smoking Risk
Tuberculosis (TB) Risk
Falls for Resident A Optimus, 3252112
Save & New
Save & Close
Clear Page
Exit Risk Assessments
Use Late Entry Option
Personal
Total Score
A resident who scores over 9 is at risk.
Page1 Page2 Page3 Page4
Medications
To assess resident, consider the following medications taken during the last 7 days:
Antipsychotics, antianxiety, antidepressants, diuretics, anesthetics, antihistamines, antihypertensives, antiseizures, bensodiazepines, cardiovascular meds, cathartics, hypoglycemics, narcotics, hypnotics/sedatives, muscle relaxants.
Adverse Drug Reactions: sedation/fatigue/lethargy, decreased alertness, postural/orthostatic hypotenion, dizziness, decreased neuromuscular function/ataxia, decreased memory/cognitive impairment, blurred vision, confusion, arrythmias, syncope and urinary urgency.
0. No Medications Taken Currently or Within the Last 7 Days
2. 1-2 Medications Taken Currently or Within the Last 7 Days (Review ADRs)
4. 3 or More Medications Taken Currently or Within the Last 7 Days (Review ADRs)
Consider environmental risk factors in resident's interventions.
Consider the addition or removal of balance mobility devices and/or pacemakers.

Appendix 5: Quality Measure Tip Sheet

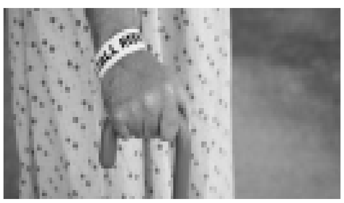
Quality Measure Tip Sheet: Falls With Major Injury—Long Stay

Quality Measure Overview

- This measure is a look-back scans measure. If the resident had one or more falls with a major injury on one or more of the look-back scan assessments, it will trigger the measure.
- Measure triggers if the event/condition occurred any time during a one-year period.
- Fall history is obtained with a look-back of up to six months prior to admission.

Exclusions:

- The occurrence of fall was not assessed.
- The assessment indicates that a fall occurred and that the number of falls with major injury was not assessed.



MDS Coding Requirements

In the Minimum Data Set (MDS):

- Include fall history on admission/entry or re-entry.
- Include number of falls since admission/entry, re-entry, or prior assessment (Omnibus Reconciliation Act [OBRA] or scheduled Medicare Prospective Payment System assessment)—whichever is more recent.
- Indicate major injuries for:
  - Bone fractures.
  - Joint dislocations.
  - Closed head injuries with altered consciousness.
  - Subdural hematoma.

Ask These Questions...

- Was the MDS coded as per the *Resident Assessment Instrument* requirements?
- Was a fall risk assessment completed on admission, quarterly, and with changes to identify appropriate risk?
- Was a process in place (based on fall score) to initiate preventive devices?
- Were preventive devices communicated to direct-care staff members?
- Are interventions monitored for placement and function?
- Are gait belts accessible for transfers?
- Do the nurses demonstrate competence for assessing fall risk?
- Are the direct-care staff members proficient in transfers and mobility functions?
- Are fall precautions taken if the resident is on anticoagulants, antidepressants, antiepileptics, antihypertensives, antiparkinson agents, benzodiazepines, diuretics, nonsteroidal anti-inflammatory agents, psychotropics, vasodilators, laxatives, glycemic medications, tranquilizers, or hypnotics/sedatives?
- Are vision issues addressed?
- Is appropriate footwear used?
- Is the resident appropriately positioned?
- Are pain and comfort issues addressed?
- Are rest periods provided?
- Are activity programs individualized for the resident to meet his or her needs/preferences?
- Is continence managed?

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ALLIANT QUALITY

This material from Health Services Advisory Group, Inc. was adapted by GMCF, for Alliant Quality, the Medicare Quality Innovation Network – Quality Improvement Organization for Georgia and North Carolina, under contract with the Centers for Medicare & Medicaid Services (CMS), an agency of the U.S. Department of Health and Human Services. The contents presented do not necessarily reflect CMS policy. Publication No. 11SOW-GMCFQIN-C2-16-53

Appendix 6:

A Hierarchy of Medications by Fall Risk (highest risk first)

Anticholinergics

Antiparkinsonian agents

- benztropine (Cogentin®)
- trihexyphenidyl (Artane®)

Sedating Antihistamines (many combination products available; check labels)

- brompheniramine (various cough/cold/allergy products)
- carbinoxamine (various cough/cold/allergy products)
- chlorpheniramine (Chlor-Trimeton®, various)
- clemastine (Tavist®, various)
- cyproheptadine (Periactin®)
- dexbrompheniramine (various cough/cold/allergy products)
- dexchlorpheniramine (various cough/cold/allergy products)
- dimenhydrinate
- diphenhydramine, oral (Benadryl®)
- doxylamine (Unisom®, various)
- hydroxyzine (Atarax®, Vistaril®)
- meclizine
- prochlorperazine
- promethazine (Phenergan®, various)
- triprolidine (various cough/cold/allergy products)

Antimuscarinics

- oxybutynin (Ditropan®)
- tolterodine (Detrol®)
- trospium (Sanctura®)
- solifenacin (Vesicare®)
- darifenacin (Enablex®)
- flavoxate
- fesoterodine (Toviaz®)

Antispasmodics

- atropine (various combinations)
- belladonna alkaloids (various combinations)
- dicyclomine (Bentyl®)
- hyoscyamine (Levsin®, Lesinex®)
- propantheline (generic only)
- homatropine
- scopalamine (Tranderm Scop®)
- clidinium/chlordiazepozide (Librax®)
- atropine/hyoscyamine/phenobarbital/scopolamine (Donnatal®)
- hyoscyamine/methenamine/phenyl salicylate (Urised®, Prosed®)

Skeletal muscle relaxants

- carisoprodol (Soma®)
- chlorzoxazone (Parafon Forte DSC®)
- cyclobenzaprine (Flexeril®)
- metaxalone (Skelaxin®)
- methocarbamol (Robaxin®)
- orphenadrine (Norflex®)
- tizanidine (Zanaflex®)

Psychotropic agents

Benzodiazepines

- alprazolam (Xanax®)
- chlordiazepoxide (Librium®)
- clonazepam (Klonopin®)
- clorazepate (Tranxene®)
- diazepam (Valium®)
- lorazepam (Ativan®)
- oxazepam (Serax®)

Hypnotics

- estazolam (ProSom®)
- eszopiclone (Lunesta®)
- flurazepam (Dalmane®)
- quazepam (Doral®)
- temezepam (Restoril®)
- triazolam (Halcion®)
- zaleplon (Sonata®)
- zolpidem (Ambien®)

Antipsychotics

- chlorpromazine (Thorazine®)
- fluphenazine (Prolixin®)
- haloperidol (Haldol®)
- loxapine (Loxitane®)
- molindone (Moban®)
- perphenazine (Trilafon®)
- thioridazine (Mellaril®)
- thiothixene (Navane®)
- trifluoperazine (Stelazine®)
- aripiprazole (Abilify®)
- asenapine (Saphris®)
- clozapine (Clozaril®)
- iloperidone (Fanapt®)
- olanzapine (Zyprexa®)
- paliperidone (Invega®)
- quetiapine (Seroquel®)
- risperidone (Risperda®l)
- ziprasidone (Geodon®)

Sedating Antidepressants

- paroxetine (Paxil®)
- nefazodone (Serzone®)
- trazodone (Desyrel®)
- mirtazapine (Remeron®)
- amitriptyline (Elavil®)
- clomipramine (Anafranil®)
- doxepin (Sinequan®)
- imipramine (Norpramin®)

- nortriptyline (Pamelor®)
- phenelzine (Nardil®)
- selegiline patch (Emsam®)
- tranylcypromine (Parnate®)
- amoxapine
- desipramine
- protriptyline
- trimipramine

Analgesics

Opioids

- morphine (Roxano®l, MS Contin®, Avinza®, Kadian®)
- hydromorphone (Dilaudid®)
- oxymorphone (Opana®)
- levorphanol (generic only)
- codeine (generic only)
- codeine/APAP (Tylenol #3®)
- hydrocodone/APAP (Lortab®, Lorcet®, Vicodin®)
- oxycodone (Roxicodone®, Oxy IR®, Oxycodone®)
- oxycodone/APAP (Percocet®)
- meperidine (Demerol®)
- fentanyl (Duragesic®)
- methadone (Dolophine®)
- pentazocine (Talwin®)
- butorphanol (Stadol®)
- nalbuphine (Nubain®)
- buprenorphine (Buprenex®)

Central analgesics

- tramadol (Ultram®)
- tramadol/APAP (Ultracet®)
- tapentadol (Nucynta®)

NSAIDs

- celecoxib (Celebrex®)
- diclofenac (Voltaren®, Cataflam®, Flector®)
- diflunisal (Dolobid®)
- etodolac (Lodine®)
- fenoprofen (Nalfon®)
- ibuprofen (Motrin®, Advil®)
- ketoprofen (Orudis®, Oruvail®)
- meclofenamate (Meclomen®)
- mefenamic acid (Ponstel®)
- meloxicam (Mobic®)
- nabumetone (Relafen®)
- naproxen (Naprosyn®, Anaprox®, Aleve®)
- oxaprozin (Daypro®)
- piroxicam (Feldene®
- sulindac (Clinoril®)
- tolmetin (Tolectin®)

Anticonvulsants

- carbamazepine (Tegretol®)
- ethosuximide (Zarontin®)
- felbamate (Felbatol®)
- gabapentin (Neurontin®)
- lacosamide (Vimpat®)
- lamotrigine (Lamictal®)
- levitiracetam (Keppra®)
- oxcarbazepine (Trileptal®)
- phenobarbital (generic only)
- phenytoin (Dilantin®)
- pregabalin (Lyrica®)
- primidone (Mysoline®)
- tiagabine (Gabitril®)
- topiramate (Topamax®)
- valproic acid (Depakote®, Depakene®)
- vigabatrin (Sabril®)
- zonisamide (Zonegran®)

Cardiovascular agents

Beta-blockers

- atenolol (Tenormin®)
- atenolol/chlorthalidone (Tenoretic®)
- bisoprolol (Zebeta®)
- bisoprolol/HCTZ (Ziac®)
- metoprolol (Lopressor®, Toprol XL®)
- metoprolol/HCTZ (Lopressor HCT®)
- nadolol (Corgard®)
- nadolol/bendroflumethazide (Corzide®)
- propranolol (Inderal®)
- acebutolol (Sectral®)
- pindolol (Visken®)
- carvedilol (Coreg®)
- labetalol (Normodyne®, Trandate®)
- nebivolol (Bystolic®)

Alpha-blockers

- doxazosin (Cardura®)
- terazosin (Hytrin®)
- prazosin (Minipress®)

Calcium channel blockers

- amlodipine (Norvasc®)
- felodipine (Plendil®)
- isradipine (DynaCirc®)
- nicardipine (Cardene)
- nifedipine (Procardia®, Adalat®, Nifedical®)
- nidoldipine (Sular®)
- diltiazem (Cardizem®, Cartia®, Dilacor®, Diltia®, Tiazac®, Taztia®)
- verapamil (Calan®, Isoptin®, Verelan®, Covera®)

Antiarrhythmics

- Quinidine (generic only)
- procainamide (Pronestyl®, Procan®)
- disopyramide (Norpace®)
- mexiletine (Mexitil®)
- flecainide (Tambocor®)
- propafenone (Rhythmol®)
- amiodarone (Cordarone®)
- dofetilide (Tikosyn®)
- dronedarone (Multaq®)
- sotalol (Betapace®)
- ibutilide (Corvert®)

Central alpha2-agonists

- clonidine (Catapres®)
- methyldopa (Aldomet®)

Peripheral adrenergic antagonists

- reserpine (generic only)

Direct arterial vasodilators

- minoxidil (Loniten®)
- hydralazine (Apresoline®)

Inotropic agents

- digoxin (Lanoxin®)

metoclopramide (Reglan®)

Other Antidepressants

- Citalopram (Celexa®)
- Dexvenlafaxine (Prestiq®)
- Duloxetine (Cymbalta®)
- Escitalopram (Lexapro®)
- Fluoxetine (Prozac®)
- Sertraline (Zoloft®)
- Venlafaxine (Effexor®)

Diuretics

- chlorthalidone (Hygroton®)
- hydrochlorothiazide (HydroDiuril®, Microzide®)
- indapamide (Lozol®)
- metolazone (Zaroxolyn®)
- bumetanide (Bumex®)
- furosemide (Lasix®)
- torsemide (Demadex®)
- spironolactone (Aldactone®)
- spironolactone/HCTZ (Aldactazide®)
- amiloride (Midamor®)

Laxatives

- Bisacodyl
- Magnesium Citrate
- Magnesium Hydroxide (Milk of Magnesia)
- Mineral Oil
- Senna

Antidiabetic agents

Insulin

- insulin lispro (Humalog®)
- insulin protamine lispro/lispro (Humalog 75/25®, Humalog 50/50®)
- insulin protamine aspart/aspart (Novolog 70/30®)
- insulin aspart (Novolog®)
- insulin glulisine (Apidra®)
- insulin regular (Humulin R®, Novolin R®)
- insulin NPH (Humulin N®, Novolin N®)
- insulin NPH/regular (Humulin 70/30®, Novolin 70/30®)
- insulin glargine (Lantus®)
- insulin detemir (Levemir®)
- insulin

Sulfonylureas

- glipizide (Glucotrol®)
- glyburide (DiaBeta®, Micronase®)
- glyburide, micronized (Glynase®)
- glimepiride (Amaryl®)

Meglitinides

- nateglinide (Starlix®)
- repaglinide (Prandin®)

List compiled from:

Agency for Healthcare Research and Quality. (2013) Medication Fall Risk Score and Evaluation Tools. Retreived 10/5/2017 from https://www.ahrq.gov/professionals/systems/hospital/fallpxtoolkit/fallpxtk-tool3i.html

American Geriatrics Society. (2015) Updated Beers Criteria for Potentially Inappropriate Medication Use in Older Adults. *Journal of the American Geriatrics Society*. DOI:10.1111/jgs.13702

Sobeski, L. (2013) Table of Medications that Increase Fall Risk. Retrieved 10/5/2017 from https://www.unmc.edu/patient-safety/_documents/meds-with-fall-risk-brand-generic-table-2013.pdf

Appendix 7: Tables from Loretto database

List of tables from the Loretto database:

1. ADTHistory (Admission, discharge, and transfer dates and times)
2. Behavior-Incident (Observed resident behavior incidents)
3. Behavior-Summary (Summary of resident behaviors)
4. Bowel_and_Bladder (Records regarding bowel and bladder)
5. Braden (Pressure sore risk evaluation)
6. Demographics_Only (Resident demographics only)
7. Falls (Fall events)
8. Falls_risk (Fall risk evaluation)
9. Finance (Financial information)
10. General_Admission_Observation (Observations recorded about the resident from admission)
11. Hospital (Mostly empty table)
12. ICD10 (ICD9 and ICD10 codes recorded along with resident id)
13. Immunizations (Immunization records)
14. MDS_30 (Minimum Data Set (MDS) 3.0 standardized resident assessment)
15. Norton (Pressure sore risk evaluation)
16. NortonPlus (Pressure sore risk evaluation plus evaluation of other patient factors, only 152 records)
17. Orders (Mostly empty table)
18. PHQ (Patient Health Questionnaire (PHQ) for evaluating depression risks)
19. Progress_Notes (Notes about residents)
20. Skinwound (Records of resident skin wounds)
21. Vital_Signs (Records of resident vital signs)
22. Weight_Loss (Mostly empty table)

Appendix 8: Sample SQL used for data analysis.

Sample SQL code for combining data between the tables.

```
SELECT DISTINCT(F.ID), F.resident_id, F.fallct,
F.falldt, F.visstat, F.cogstatchg, F.cogstatbeh, F.cont, F.balance, F.mobil, F.sysbp, F.temp, F.resp, F.age, F.healthcon, F.meds,
F.total,
DateValue(F.create_dt) as CreateDate, 'Fall' AS Fall
FROM Falls_risk as F Inner Join ADTFall as A
On F.resident_id = A.resident_id
WHERE (F.resident_id)<>1001 AND DateValue(F.create_dt) Between A.AdmitDt AND A.DischargeDate;

SELECT Bronchopulmonary.resident_id, Bronchopulmonary.Field_Name, Bronchopulmonary.create_dt, 'NoFall' AS Fall INTO
BronchoPulmNoFall
FROM Bronchopulmonary
        WHERE (Bronchopulmonary.resident_id) Not In (SELECT DISTINCT(ADTFall.resident_id) FROM ADTFall) And
        (Bronchopulmonary.resident_id)<>1001
        And (Bronchopulmonary.Field_Name) In ('Anxiety', 'Bradycardia', 'Chest Pain', 'Cyanosis', 'Dyspnea', 'Fever',
        'Hypertensive', 'Hypotensive', 'Lethargy', 'Pulse oximeter <90%', 'Rapid respirations', 'Restlessness', 'Short of Breath',
        'Tachycardia')
Order By Bronchopulmonary.Field_Name;
```

Sample SQL code for transforming "age on admission" to a nominal variable:

```
SELECT SWITCH(AgeOnAdmit >95, "Over95",
AgeOnAdmit Between 90 AND 95, "Between90-95",
AgeOnAdmit Between 85 AND 89, "Between85-89",
AgeOnAdmit Between 80 AND 84, "Between80-84",
AgeOnAdmit Between 70 AND 79, "Between70-79",
AgeOnAdmit Between 60 AND 69, "Between60-69",
True, "LessThan60") AS AgeRange,
X.*
FROM GenAdmAll as X;
```

SQL code used for creating the final table with all permutations of various measures from ICD, Fall Assessment, General Admission, and Norton tables (NOTE, by linking tables in the following manner, there was a resultant "resampling" of individuals that may have multiple different records in each table. The resulting table had 58237 "Fall" records and 47891 "NoFall" records adding a natural balance to the final table with the tradeoff of redundant data.):

```
SELECT FallGridWithID.*, GenAdmAge.* INTO ICDGenAdm
FROM FallGridWithID INNER JOIN GenAdmAge
ON FallGridWithID.Resident_id = GenAdmAge.resident_id;


SELECT Y.*, X.* INTO ICDFallAssessGen
FROM ICDGenWithDates AS X INNER JOIN FallAssessAll AS Y
ON X.resident_id = Y.resident_id
AND DateValue(Y.CreateDate) <= DateValue(X.DischargeDate) AND DateValue(Y.CreateDate) >= DateValue(X.AdmitDt);


SELECT Y.physcon AS NortonPhyscon, Y.mencon AS NortonMencon, Y.activ AS NortonActiv, Y.mobil AS NortonMobil, Y.incont
AS NortonIncont, Y.total AS NortonTotal, X.*
FROM ICDFallAssessGen AS X INNER JOIN Norton AS Y
ON X.resident_id = Y.resident_id
AND DateValue(Y.Create_dt) <= DateValue(X.DischargeDate) AND DateValue(Y.Create_dt) >= DateValue(X.AdmitDt);
```

Appendix 9: Weka output for Decision Tree

=== Model information ===

Filename: FallModelTreeRandomTreeSimple.model

Scheme: weka.classifiers.trees.RandomTree -K 4 -M 150.0 -V 0.001 -S 1 -depth 3

Relation: ICDNortonFallGenWekaTrain-weka.filters.unsupervised.attribute.Remove-R1,4-6,8-11,14-16,18-19,21-90,92-111

Attributes: 9

NortonMencon
NortonActiv
FA_fallct
FA_balance
FA_mobil
FA_age
FA_total
AgeRange
Fall

=== Classifier model ===

RandomTree

Size of the tree : 50

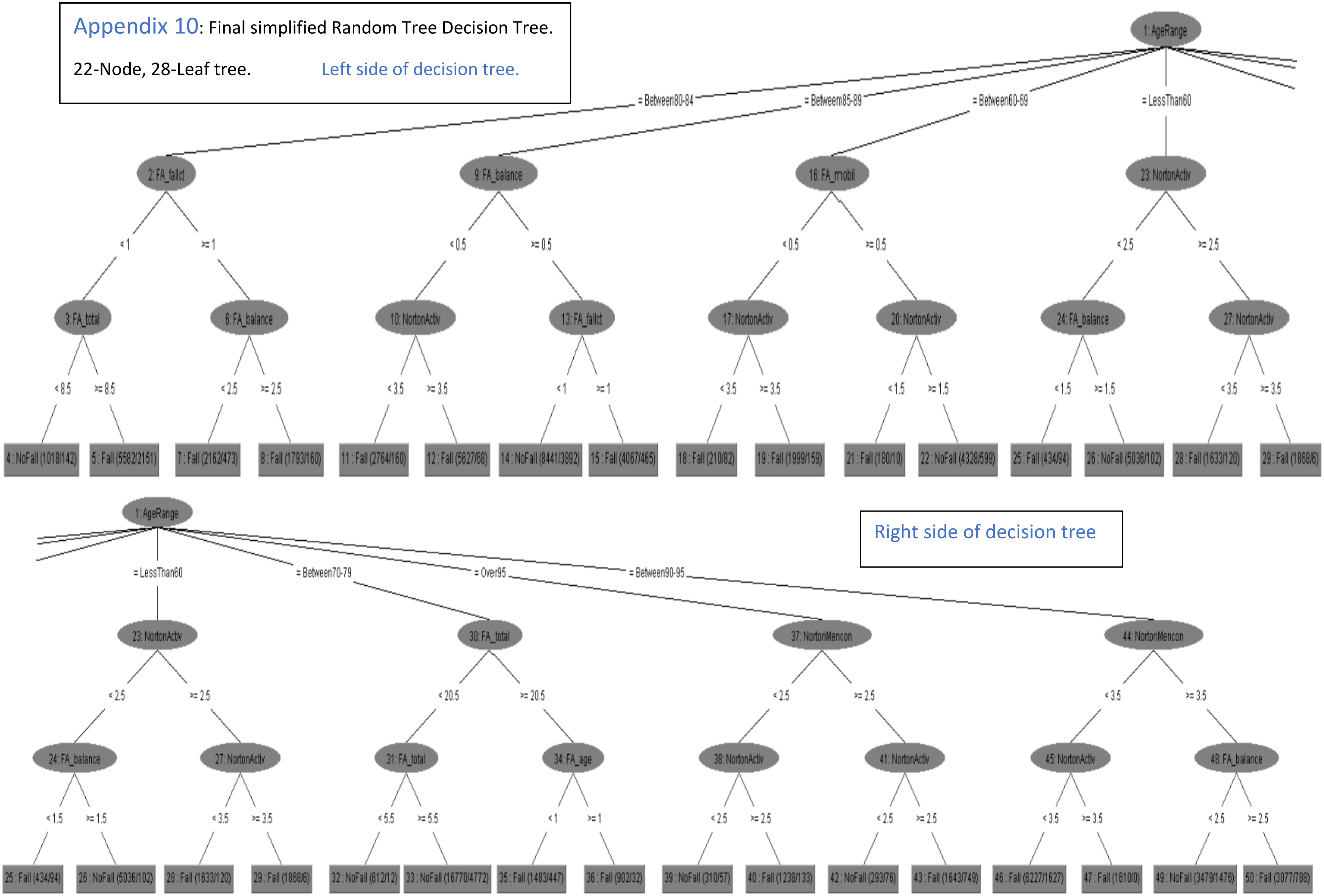
Max depth of tree: 3

Visualization of the Decision Tree is on the next page.

```
AgeRange = Between80-84
|  FA_fallct < 1
|  |  FA_total < 8.5 : NoFall (1018/142)
|  |  FA_total >= 8.5 : Fall (5582/2151)
|  FA_fallct >= 1
|  |  FA_balance < 2.5 : Fall (2162/473)
|  |  FA_balance >= 2.5 : Fall (1793/160)
AgeRange = Between85-89
|  FA_balance < 0.5
|  |  NortonActiv < 3.5 : Fall (2764/160)
|  |  NortonActiv >= 3.5 : Fall (5627/68)
|  FA_balance >= 0.5
|  |  FA_fallct < 1 : NoFall (8441/3892)
|  |  FA_fallct >= 1 : Fall (4067/465)
AgeRange = Between60-69
|  FA_mobil < 0.5
|  |  NortonActiv < 3.5 : Fall (210/82)
|  |  NortonActiv >= 3.5 : Fall (1999/159)
|  FA_mobil >= 0.5
|  |  NortonActiv < 1.5 : Fall (180/10)
|  |  NortonActiv >= 1.5 : NoFall (4328/599)
AgeRange = LessThan60
|  NortonActiv < 2.5
|  |  FA_balance < 1.5 : Fall (434/94)
|  |  FA_balance >= 1.5 : NoFall (5036/102)
|  NortonActiv >= 2.5
|  |  NortonActiv < 3.5 : Fall (1633/120)
|  |  NortonActiv >= 3.5 : Fall (1868/6)
AgeRange = Between70-79
|  FA_total < 20.5
|  |  FA_total < 5.5 : NoFall (612/12)
|  |  FA_total >= 5.5 : NoFall (16770/4772)
|  FA_total >= 20.5
|  |  FA_age < 1 : Fall (1483/447)
|  |  FA_age >= 1 : Fall (902/32)
AgeRange = Over95
|  NortonMencon < 2.5
|  |  NortonActiv < 2.5 : NoFall (310/57)
|  |  NortonActiv >= 2.5 : Fall (1238/133)
|  NortonMencon >= 2.5
|  |  NortonActiv < 2.5 : NoFall (293/76)
|  |  NortonActiv >= 2.5 : Fall (1643/749)
AgeRange = Between90-95
|  NortonMencon < 3.5
|  |  NortonActiv < 3.5 : Fall (6227/1627)
|  |  NortonActiv >= 3.5 : Fall (1610/0)
|  NortonMencon >= 3.5
|  |  FA_balance < 2.5 : NoFall (3479/1476)
|  |  FA_balance >= 2.5 : Fall (3077/788)
```

Appendix 10: Final simplified Random Tree Decision Tree.

22-Node, 28-Leaf tree. Left side of decision tree.



Right side of decision tree