An Electronic Health Record Data-driven Model for Identifying Older Adults at Risk of Unintentional Falls

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Abstract

Screening for risk of unintentional falls remains low in the primary care setting because of the time constraints of brief office visits. National studies suggest that physicians caring for older adults provide recommended fall risk screening only 30 to 37 percent of the time. Given prior success in developing methods for repurposing electronic health record data for the identification of fall risk, this study involves building a model in which electronic health record data could be applied for use in clinical decision support to bolster screening by proactively identifying patients for whom screening would be beneficial and targeting efforts specifically to those patients. The final model, consisting of priority and extended measures, demonstrates moderate discriminatory power, indicating that it could prove useful in a clinical setting for identifying patients at risk of falls. Focus group discussions reveal important contextual issues involving the use of fall-related data and provide direction for the development of health systems–level innovations for the use of electronic health record data for fall risk identification.

Keywords: electronic health record data; unintentional falls; screening; prevention

Introduction

Unintentional falls among older adults are multicausal, resulting from an interaction of diverse risk factors.[1] Currently, the Timed Get-Up-and-Go test is the only screening tool recommended by the US Preventive Services Task Force (USPSTF) for determining risk of falls.[2] However, the frequency of use of this test in primary care remains low because of the time constraints of brief office visits.[3] National studies suggest that physicians caring for older adults provide recommended fall risk screening only 30 to 37 percent of the time.[4] In light of prior success in developing methods for repurposing electronic health record (EHR) data for fall risk identification,[5] applying EHR data as clinical decision support in fall risk identification may serve as a means of efficient, systematic screening and support efforts to identify older adults at risk of falls. Further, this use of data could help bolster use of the Timed Get-Up-and-Go test by proactively identifying patients for screening and targeting efforts specifically to those patients.

Background

Use of EHR data has been shown to be effective in the identification of various at-risk patient populations.[6–8] However, numerous innovations in primary care dependent on leveraging EHR data have been unsuccessful because they were introduced without providers' willingness to adopt them[9, 10] and because they lacked sensitivity to the interrelation of the innovation and the organization.[11] Given these challenges, an exploratory qualitative study was conducted in four West Virginia primary care centers to better inform the development of an EHR data-driven case-finding model. Focus groups were completed between August 2014 and January 2015. Participants included medical doctors, doctors of osteopathy, nurse practitioners, nurses, and medical assistants. The number of participants per focus group ranged from a minimum of 6 to a maximum of 15, with an average of 10 healthcare team members taking part per session. Focus group transcripts were independently coded and reviewed in a two-stage process by the primary and secondary researchers until agreement on codes and themes was reached. Stage one of the coding involved development of mutually agreed-upon themes, whereas stage two involved a further refinement and synthesis of the data into key theory-based constructs and variables necessary for analysis. The study was reviewed by the West Virginia University Institutional Review Board and granted exempt status (protocol number 1403223131).

Focus group discussions underscored that these primary care providers are under a tremendous amount of pressure to meet the needs of their patients. The collective narrative reveals a caring, dedicated healthcare team caring for older adult patients with complex healthcare needs. While fall risk identification and prevention are acknowledged as important, the deficit of resources to adequately address the care complexities of older adults within the time and energy constraints of brief office visits is a significant barrier and highlights the need for data-supported, team-based care. We find that data germane to fall risk identification are routinely collected in EHRs, providing an opportunity for model building and providing the basis for development of policies and procedures to leverage informatics for fall risk screening and prevention of falls. However, these data are not recognized as collectively pertinent to risk identification and are instead used only at the point of care in their component pieces. This scenario underscores the need for increased support and training of primary care providers to best manage and leverage EHR data for population-level care and intervention. Recognizing the potential for and benefit of repurposing routinely collected patient-level data for clinic-wide identification of at-risk patients is a prerequisite for changes in fall risk screening at the health system level.

This study explores the use of de-identified EHR data to support fall prevention. The research question is whether EHR data can be used to build and internally validate a data-driven case-finding model to identify at-risk patients. The outcome of interest is the development of a model to identify variables best suited for identification of fall risk. This advancement would help the field of fall prevention through novel use of EHR data, while facilitating care coordination and population-level management of fall risk among older patients.

Methods

This study is a nonexperimental, retrospective analysis of de-identified EHR data from two primary care center organizations, consisting of nine physical locations excluding school-based health centers and dental clinics, in partnership with the West Virginia University Office of Health Services Research (OHSR). These centers are part of a larger network of primary care centers strategically positioned in medically underserved areas in the state.[12, 13] All clinic sites use the same EHR system certified by the Certification Commission for Healthcare Information Technology. Purposive sampling was used to identify primary care organizations for inclusion. Inclusion criteria were as follows: (1) established partnership and de-identified EHR data sharing with the OHSR and (2) use of an EHR system that allows for export of the necessary data. De-identified data sharing from these centers to the OHSR was made possible through signed business associate agreements and memoranda of understanding.

The de-identified EHR data used in this analysis were initially, by nature of the source of the data and the way in which the data were exported from the EHRs, organized in a relational database schema. That said, each type of data (i.e., patient demographics, health condition, medications, services provided, and visit/vital sign information) was held in its own table. These tables were linked by two unique identifiers per patient record: (1) an auto-identifier and (2) a clinic code to ensure that potential duplicate auto-identifiers across sites were able to be accounted for and distinguished. For logistic regression analysis using JMP data analysis software, the data tables were collapsed into a composite flat file format using

Microsoft Access queries. Adhering to the “safe harbor” method of data de-identification,[14] dates of service were recorded as time intervals from the first visit date documented for each patient. Days in whole numbers were used as the relative time interval. The Appendix lists all variables included in the final data set along with their definitions, data types, modeling types, and value labels. This study was classified as non–human subjects research by the West Virginia University Office of Research Integrity and Compliance (protocol number 1402217616) because it involves secondary data that do not include information protected by the Health Insurance Portability and Accountability Act.

Current fall prevention guidelines presented in a systematic review of current USPSTF guidelines and a meta-analysis of fall risk factors among community-dwelling older adults identified the following variables as criteria used to identify fall risk: age greater than or equal to 65 years; female gender; gait or balance impairment; a history of falls; fear of falling; vision impairment; hearing impairment; diagnosis of Parkinson’s disease; dizziness/vertigo; cognitive impairment; use of a walking aid or device; current prescription for a sedative medication; current prescription for an antiepileptic medication; current prescription for an antihypertensive medication; and current use of four or more medications, also known as polypharmacy.[15, 16] Extended variables of interest identified from additional research are race (nonwhite, white); ethnicity (Hispanic, non-Hispanic); insurance source (public, private); hypertension; diabetes type 1; diabetes type 2; diabetic neuropathy; diabetic retinopathy; osteoporosis; hypotension; dementia; rheumatoid arthritis; epilepsy; muscle weakness; fall assessment; and fall guidance.[17, 18]

Univariate analysis of the demographic characteristics, health profile, services received, and medication records of the patient population was performed. Independent-sample *t*-tests and tests of independence were used to examine potential associations across variables, in particular in relation to documented falls. Nominal logistic regression with accompanying receiver operator characteristic (ROC) analysis was used to examine the collective associations of priority and extended variables in regard to documented falls among this patient population. All analyses were completed using JMP Pro version 11.0.

Results

Statistics

Univariate statistics for patient demographics, health profile, medications, and services received were generated for patients with and without documented falls (see Table 1). Results are presented in highest to lowest rank order for each data type. These same statistics were generated in prior research using a relational database schema,[19] as opposed to the flat file transformation used here. Comparison of results between analyses revealed no discrepancies, helping to validate the internal validity of the data. In general, patients tended to be between the ages of 65 and 84 years, be female, be white, not be Hispanic or Latino, and have some form of public insurance coverage. The majority of the patients were characterized as having polypharmacy (85 percent) and hypertension (70.6 percent). Less than 1 percent of patients had documentation of fall risk screening. Antihypertensive medications (44.5 percent) and medications for type 2 diabetes (23.3 percent) were the most frequently occurring medications.

Univariate statistics were also generated for the data on patients’ vital signs (height, weight, body mass index [BMI], and blood pressure) for patients with and without documented falls (see Table 2). On average, patients were overweight with a BMI of 29.3 and a relatively controlled average systolic and diastolic blood pressure of 130/74.

Given the potential for height, weight, BMI, and blood pressure to be associated with an unintentional fall, four additional variables were created to take into account the result for each of these metrics obtained closest to the date of the last documented fall. Results for height, weight, BMI, and blood pressure for patients with documentation of falls versus patients with no documentation of falls were analyzed using independent-sample *t*-tests. No significant differences in these vital signs were identified across groups.

Chi-square tests of independence were performed to examine the relation between falls and the priority and extended variables in an unadjusted sense. Table 3 displays these results. In regard to the priority variables, we were able to reject the null hypothesis and conclude that the following variables were related to falls: age category (85 years and older, 65 to 84 years), gender (female, male), gait/balance impairment, vision impairment, hearing impairment, dizziness/vertigo, cognitive impairment, sedative medication, antiepileptic medication, antihypertension medication, and polypharmacy. In regard to the extended variables, we were able to reject the null hypothesis and conclude that the following variables were related to falls: hypertension, type 2 diabetes, type 1 diabetes, osteoporosis, hypotension, dementia, rheumatoid arthritis, epilepsy, muscle weakness, and fall assessment.

Model Building

To create a robust model based on the available data, we selected a model that accounts for the priority and extended risk factors related to unintentional falls. The variables included in our model are age greater than or equal to 65 years, female gender, gait or balance impairment, history of falls, vision impairment, hearing impairment, diagnosis of Parkinson's disease, dizziness/vertigo, cognitive impairment, use of a walking aid or device, current prescription for a sedative medication, current prescription for an antiepileptic medication, current prescription for an antihypertensive medication, polypharmacy, race (nonwhite, white), insurance source (public, private), hypertension, diabetes type 1, diabetes type 2, osteoporosis, hypotension, dementia, rheumatoid arthritis, diabetic neuropathy, epilepsy, muscle weakness, diabetic retinopathy, and fall assessment.

The model was statistically significant, $\chi^2(27, N = 3{,}933) = 203.60$, $p < .0001$, indicating that the predictors, as a set, reliably distinguish between patients who have documentation of a history of falls and those who do not. Table 4 provides the chi-square value, indication of significance, odds ratio result, and 95 percent confidence interval (CI) for each of the predictor variables in the final model. Chi-square results indicate that the following variables in this combined model reliably predict fall risk status: age category, $\chi^2(1, N = 3{,}933) = 14.00$, $p < .001$; gender, $\chi^2(1, N = 3{,}933) = 5.05$, $p < .05$; dementia, $\chi^2(1, N = 3{,}933) = 10.54$, $p < .01$; rheumatoid arthritis, $\chi^2(1, N = 3{,}933) = 5.62$, $p < .05$; epilepsy, $\chi^2(1, N = 3{,}933) = 4.63$, $p < .05$; muscle weakness, $\chi^2(1, N = 3{,}933) = 4.51$ $p < .05$; and fall assessment, $\chi^2(1, N = 3{,}933) = 104.31$, $p < .0001$. For the significantly associated variables, controlling for all variables in the model, the odds ratios indicate the following:

- Patients age 85 years and older have 2.58 times higher odds of having documentation of falls compared to patients age 65 to 84 years (95 percent CI, 1.59–4.08).
- Female patients have 1.67 times higher odds of having documentation of falls compared to male patients (95 percent CI, 1.06–2.68).
- Patients with documentation of dementia have 2.91 times higher odds of having documentation of falls compared to patients without documentation of dementia (95 percent CI, 1.55–5.26).
- Patients with documentation of rheumatoid arthritis have 2.71 times higher odds of having documentation of falls compared to patients without documentation of rheumatoid arthritis (95 percent CI, 1.21–5.42).
- Patients with documentation of epilepsy have 2.73 times higher odds of having documentation of falls compared to patients without documentation of epilepsy (95 percent CI, 1.10–6.05).
- Patients with documentation of muscle weakness have 2.50 times higher odds of having documentation of falls compared to patients without documentation of muscle weakness (95 percent CI, 1.08–5.18).
- Patients with documentation of having received a fall risk assessment have 258.24 times higher odds of having documentation of falls compared to patients without documentation of having received a fall risk assessment (95 percent CI, 93.21–1,091.99).

ROC analysis indicated an increased ability of the model to discriminate between patients with documentation of falls and those without documentation of falls (area under the ROC curve [AUC] = 0.79). Model fit statistics were as follows: corrected Akaike information criterion (AICc) = 1,015.16 and Bayesian information criterion (BIC) = 1,190.50 (see Figure 1).

Discussion

The AUC calculated here indicates how well the set of risk variables, taken as a whole, discriminates between patients with and without documented falls. In our evaluation of the available EHR data, we selected a model that accounts for the priority and extended fall risk factors for increased discernment. When only the priority measures were examined, we found an AUC of 0.69, which is weak overall. Comparatively, when only the extended measures were examined, we found a larger AUC of 0.75. Because the AUC is a measure of discernibility of the model, this larger value indicates the added value, in our patient population, of looking beyond the priority measures identified by the USPSTF and in a recent systematic review to a set of secondary measures identified in the literature on falls among older adults. When considering the priority and extended measures in combination, we found an overall AUC of 0.79, demonstrating moderate discriminatory power and making the model more apt to be useful in a clinical setting. The increase in the AUC across these models is telling in terms of the value of the variable sets independently and the greater collective value of the combined variable sets. Furthermore, the factors included in this model are more reflective of the primary causes of falls among older adults in Appalachia, giving this approach potentially stronger clinical applications in this region. We find that patients who are age 85 years and older, are female, have specific diagnoses (dementia, rheumatoid arthritis, epilepsy, and muscle weakness), and have received fall risk assessments in the past should be prioritized for screening for the risk of unintentional falls and for follow-up. This list of targeted factors could be useful for primary care efforts in triaging priority, high-risk patients. Notably, the high odds ratio for documentation of fall risk assessment and documentation of falls can be explained by the very few number of patients with documented fall risk assessments. More specifically, 16 of 22 patients (72.7 percent) with assessments had a documented fall, which is much higher than the 3.4 percent in the overall population. This finding implies that those few patients were identified by their providers as being at increased risk for a fall, and indeed a fall was documented.

One primary limitation of this study is in the documentation of EHR data, such as miscoding, potential missing fall data, and limitations in data sharing from hospitals and other care locations where fall information may have been recorded. Additionally, we are unable to develop a point-based algorithm to identify fall risk based on current USPSTF guidelines and the meta-analysis on fall risk factors because our data included too few documented fall cases. Nonetheless, we can still accurately describe the association among priority and extended variables in regard to documented falls. The strength of this study is its practical importance to public health: it facilitates the identification of a sector of the patient population at increased risk of falls in a way that is efficient and data-driven in light of the demands of primary care.

Conclusions

Increased public health efforts are needed to help foster a system-based approach to fall risk identification and prevention in primary care. The complex healthcare needs of older adults, combined with brief office visits, result in challenges that can be addressed by enhancing the application of routinely collected data. At a minimum, the model developed here can be used in the development of decision support tools to bolster use of the Timed Get-Up-and-Go test by proactively identifying patients for whom screening would be beneficial and targeting efforts specifically to those patients. Further value can be added by leveraging EHR data to expand beyond the priority fall risk factors. Repurposing EHR data allows for a broader look at fall risk factors in a way that is sensitive to the time constraints of the routine office visit and complementary to the efforts in primary care to best use data for population health and ultimately to reduce healthcare costs. In effect, this data-driven approach to fall risk identification allows for a broader scope in risk identification with increased discernment while also providing an opportunity to address low rates of fall risk screening. We therefore recommend, for the Appalachian population studied, that clinical decision support based on the findings of this study be incorporated into EHRs to enable enhanced team-based care for patients at risk of unintentional falls.

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Notes

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Table 1

Demographics, Health Profile, Medications, and Services Data for Active Patients Age 65 and Older by Falls Status and Overall

Factor		Patients with Documented Falls		Patients without Documented Falls		Total	
		Number	Percent	Number	Percent	Number	Percent
Active patients age 65 years and older		133	3.4	3,800	96.6	3,933	100.0
Demographics							
Age	65–84 years	101	2.6	3,411	86.7	3,512	89.3
	85 years and older	32	0.8	389	9.9	421	10.7
Gender	Female	97	2.5	2,314	58.8	2,411	61.3
	Male	36	0.9	1,486	37.8	1,522	38.7
Race	White	129	3.3	3,636	92.4	3,765	95.7
	Nonwhite	4	0.1	164	4.2	168	4.3
Ethnicity	Not Hispanic/Latino	133	3.4	3,766	95.8	3,899	99.1
	Hispanic/Latino	0	0.0	27	0.7	27	0.7
	Unreported or refused to report	0	0.0	7	0.2	7	0.2
Insurance source	Public	97	2.5	2,658	67.6	2,755	70.0
	Private	36	0.9	1,142	29.0	1,178	30.0
Health profile							
Polypharmacy		127	3.2	3,216	81.8	3,343	85.0
Hypertension		109	2.8	2,666	67.8	2,775	70.6
Diabetes type 2		52	1.3	1,140	29.0	1,192	30.3
Dizziness/vertigo		37	0.9	577	14.7	614	15.6
Osteoporosis		35	0.9	506	12.9	541	13.8
Hearing impairment		27	0.7	488	12.4	515	13.1
Vision impairment		29	0.7	441	11.2	470	11.9
Gait/balance impairment		21	0.5	183	4.7	204	5.2
Hypotension		12	0.3	177	4.5	189	4.8
Dementia		20	0.5	150	3.8	170	4.3
History of falls		133	3.4	0	0.0	133	3.4
Diabetes type 1		9	0.2	119	3.0	128	3.2
Cognitive impairment		9	0.2	101	2.6	110	2.8
Rheumatiod arthritis		9	0.2	98	2.5	107	2.7
Diabetic neuropathy		5	0.1	101	2.6	106	2.7
Epilepsy		9	0.2	80	2.0	89	2.2
Muscle weakness		9	0.2	83	2.1	92	2.3
Parkinson’s disease		2	0.1	52	1.3	54	1.4
Diabetic retinopathy		2	0.1	48	1.2	50	1.3
Walking aid		1	0.0	5	0.1	6	0.1
Fear of falling		0	0.0	1	0.0	1	0.0
Services received							

Fall assessment	16	0.4	4	0.1	20	0.5
Fall guidance	0	0.0	2	0.1	2	0.1
Medications						
Antihypertensive medication	76	1.9	1,674	42.6	1,750	44.5
Diabetes type 2 medication	36	0.9	882	22.4	918	23.3
Osteoporosis medication	32	0.8	742	18.9	774	19.7
Rheumatiod arthritis medication	33	0.8	594	15.1	627	15.9
Antiepileptic medication	29	0.7	568	14.4	597	15.2
Sedative medication	17	0.4	277	7.0	294	7.4
Vertigo medication	16	0.4	261	6.6	277	7.0
Diabetes type 1 medication	17	0.4	256	6.5	273	6.9
Parkinson’s medication	11	0.3	137	3.5	148	3.8
Dementia medication	1	0.0	7	0.2	8	0.2
Hypotension medication	0	0.0	3	0.1	3	0.1

Table 2

Data on Vital Signs for Active Patients Age 65 Years and Older by Fall Status and Overall

Vital Signs	Patients with Documented Falls		Patients without Documented Falls		Total		t (p)
	Mean (SD)	Percent Missing	Mean (SD)	Percent Missing	Mean (SD)	Percent Missing	
Height (in.)	64.5 (4.2)	3.8	65.5 (3.9)	8.1	65.4 (4.0)	8.0	2.76 (<.01)
Weight (lb.)	172.1 (44.6)	0.75	178.8 (42.9)	3.0	178.6 (43.0)	3.0	1.79 (>.05)
Body mass index	29.0 (6.4)	3.8	29.3 (6.4)	8.4	29.3 (6.4)	8.3	0.48 (>.05)
Systolic blood pressure (mm Hg)	130.7 (29.9)	0.0	130.1 (17.3)	1.3	130.1 (17.9)	1.3	0.35 (>.05)
Diastolic blood pressure (mm Hg)	73.3 (17.8)	0.0	73.9 (10.2)	1.3	73.9 (10.6)	1.3	0.67 (>.05)

Table 3

Chi-Square Tests of Independence for Falls

Variables	χ^2	*p*	Odds Ratio (95% CI)
Priority measures			
Age category (85 years and older; 64–85 years)	25.69	<.00****	0.36 (0.24–0.54)
Gender (female; male)	7.85	.01*	0.58 (0.39–0.85)
Gait/balance impairment	31.47	<.00****	3.71 (2.27–6.04)
Vision impairment	12.70	.00***	2.12 (1.39–3.24)
Hearing impairment	6.28	.01*	1.73 (1.12–2.67)
Parkinson's disease	0.017	.90	1.10 (0.27–4.57)
Dizziness/vertigo	15.57	<.00****	2.15 (1.46–3.18)
Cognitive impairment	7.98	.00*	2.66 (1.31–5.38)
Walking aid	3.25	.07	5.75 (0.67–49.56)
Sedative medication	5.61	.02*	1.86 (1.10–3.15)
Antiepileptic medication	4.69	.03*	0.63 (0.41–0.96)
Antihypertension medication	8.92	.00**	1.69 (1.19–2.40)
Polypharmacy	11.88	.00***	3.84 (1.69–8.76)
Fear of falling	0.035	.85	0.00
Extended measures			
Race (nonwhite; white)	0.54	.46	0.69 (0.25–1.88)
Ethnicity (Hispanic; non-Hispanic)	0.95	.33	0.00
Insurance source (public; private)	0.55	.46	1.16 (0.78–1.71)
Hypertension	8.61	.00**	1.93 (1.24–3.02)
Diabetes type 2	5.04	.02*	1.50 (1.05–2.14)
Osteoporosis	18.31	<.00****	2.32 (1.56–3.46)
Hypotension	5.351	.02*	2.03 (1.10–3.74)
Dementia	38.22	<.00****	4.31 (2.61–7.12)
Diabetes type 1	5.39	.02*	2.25 (1.11–4.52)
Rheumatoid arthritis	8.52	.00**	2.74 (1.35–5.55)
Diabetic neuropathy	0.60	.44	1.43 (0.57–3.57)
Epilepsy	12.63	.00***	3.38 (1.66–6.88)
Muscle weakness	11.81	.00***	3.25 (1.60–6.62)
Diabetic retinopathy	0.06	.81	1.19 (0.29–4.96)
Fall assessment	361.18	<.00****	129.78 (42.73–394.18)
Fall guidance	0.07	.79	0

Note: N = 3,933 and df = 1 for all measures except ethnicity, for which N = 3,926 and df =1.
*$p < .05$, **$p < .01$, ***$p < .001$, ****$p < .0001$.

Table 4

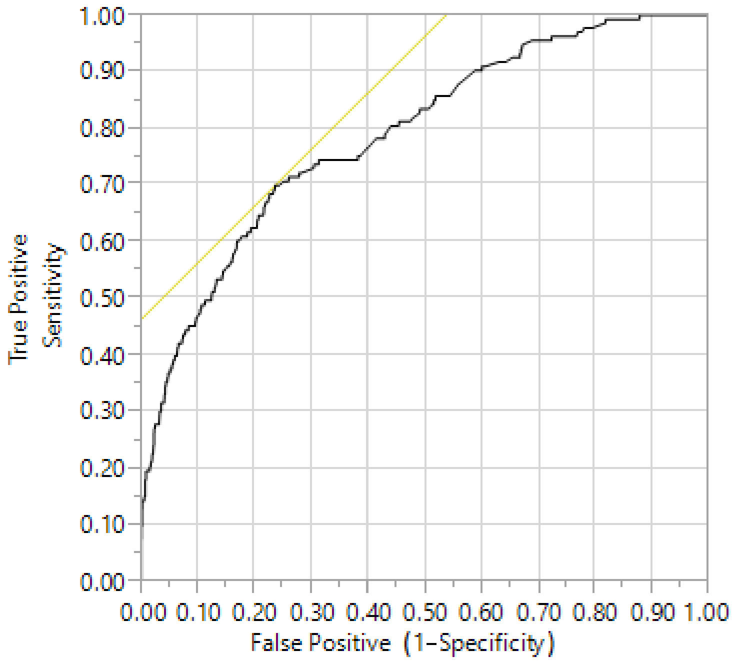
Nominal Logistic Regression Results: Model with Priority and Extended Fall Risk Variables

Variables	χ^2	***p***	**Odds Ratio (95% CI)**
Age category (85 and older; 64–85)	14.00	.00***	2.58 (1.59–4.08)
Gender (female; male)	5.05	.02*	1.67 (1.06–2.68)
Gait/balance impairment	1.13	.29	1.40 (0.74–2.53)
Vision impairment	3.07	.08	1.57 (0.94–2.51)
Hearing impairment	0.20	.65	1.12 (0.66–1.84)
Parkinson’s disease	2.28	.13	0.31 (0.04–1.34)
Dizziness/vertigo	1.33	.25	1.31 (0.82–2.03)
Cognitive impairment	0.01	.94	0.97 (0.40–2.10)
Walking aid	1.03	.31	3.82 (0.18–27.66)
Sedative medication	0.04	.83	1.07 (0.56–1.89)
Antiepileptic medication	0.31	.57	0.77 (0.28–1.80)
Antihypertension medication	1.75	.19	1.31 (0.88–1.98)
Polypharmacy	2.93	.09	2.09 (0.91–5.85)
Race (nonwhite; white)	1.97	.16	2.15 (0.76–8.34)
Insurance source (public; private)	0.30	.58	1.13 (0.74–1.76)
Hypertension	0.11	.74	1.01 (0.66–1.85)
Diabetes type 1	0.86	.35	1.47 (0.63–3.07)
Diabetes type 2	1.20	.27	1.27 (0.82–1.94)
Osteoporosis	2.06	.15	1.40 (0.88–2.20)
Hypotension	0.31	.58	1.22 (0.59–2.31)
Dementia	10.54	.00**	2.91 (1.55–5.26)
Rheumatoid arthritis	5.62	.02*	2.71 (1.21–5.42)
Diabetic neuropathy	0.08	.78	1.15 (0.38–2.82)
Epilepsy	4.63	.03*	2.73 (1.10–6.05)
Muscle weakness	4.51	.03*	2.50 (1.08–5.18)
Diabetic retinopathy	1.03	.31	0.48 (0.07–1.79)
Falls assessment	104.31	<.00****	258.24 (93.21–1,091.99)

Note: N = 3,933 and df = 1 for all analyses.
*p <.05, **p < .01, ***p < .001, ****p < .0001.

Figure 1

Receiver Operator Characteristic (ROC) Results: Final Model with Priority and Extended Fall Risk Variables (Area under the Curve [AUC] = 0.79)



**Note:* The arch line, indicating the receiver operator characteristic curve, represents the ability of the model to discriminate between patients with documentation of falls and those without documentation of falls. The yellow line marks a good cutoff point under the assumption that sensitivity and specificity are balanced.

Appendix

Data Dictionary

Variable Name	Variable Definition	Data Type	Modeling Type	Value Labels
Patient_ID	Patient ID (unique, de-identified patient identifier linked with clinic code)	Numeric	Nominal	–
clinic_code	Clinic code (code for location at which patient is seen, linked with Patient_ID)	Numeric	Nominal	–
Age	Age (continuous)	Numeric	Ordinal	–
Gender	Gender	Numeric	Nominal	0 = Female; 1 = Male
Race	Race	Numeric	Nominal	0 = White; 1 = Nonwhite
Ethnicity	Ethnicity	Numeric	Nominal	0 = Not Hispanic/Latino; 1 = Hispanic/Latino
Insurance_source	Insurance source	Numeric	Nominal	0 = Private; 1 = Public
Payor_category	Insurance payor category	Numeric	Nominal	0 = Non–managed care; 1 = Managed care
FallsAsmt	Documented falls assessment	Numeric	Nominal	0 = No falls assessment; 1 = Falls assessment
FallsAsmt_Year	Year in which falls assessment was last documented	Numeric	Ordinal	–
FallsGuidance	Documented falls guidance	Numeric	Nominal	0 = No falls guidance; 1 = Falls guidance
FallsGuidance_Year	Year in which falls guidance was last documented	Numeric	Ordinal	–
Hypertension	Documented hypertension	Numeric	Nominal	0 = No hypertension; 1 = Hypertension
Hypertension_Year	Year in which hypertension was last documented	Numeric	Ordinal	–
Dementia	Documented dementia	Numeric	Nominal	0 = No dementia; 1 = Dementia

Dementia_Year	Year in which dementia was last documented	Numeric	Ordinal	–
Polypharmacy	Identified polypharmacy	Numeric	Nominal	0 = No polypharmacy; 1 = Polypharmacy
Polypharmacy_Year	Year in which polypharmacy was last identified	Numeric	Ordinal	–
Osteoporosis	Documented osteoporosis	Numeric	Nominal	0 = No osteoporosis; 1 = Osteoporosis
Osteoporosis_Year	Year in which osteoporosis was last documented	Numeric	Ordinal	–
CognitiveImp	Documented cognitive impairment	Numeric	Nominal	0 = No cognitive impairment; 1 = Cognitive impairment
CognitiveImp_Year	Year in which cognitive impairment was last documented	Numeric	Ordinal	–
MuscleWeakness	Documented muscle weakness	Numeric	Nominal	0 = No muscle weakness; 1 = Muscle weakness
MuscleWeakness_Year	Year in which muscle weakness was last documented	Numeric	Ordinal	–
HearingImp	Documented hearing impairment	Numeric	Nominal	0 = No hearing impairment; 1 = Hearing impairment
HearingImp_Year	Year in which hearing impairment was last documented	Numeric	Ordinal	–
Arthritis	Documented arthritis	Numeric	Nominal	0 = No arthritis; 1 = Arthritis
Arthritis_Year	Year in which arthritis was last documented	Numeric	Ordinal	–
Dizziness-Vertigo	Documented dizziness/vertigo	Numeric	Nominal	0 = No dizziness/vertigo; 1 = Dizziness/vertigo

Dizziness-Vertigo_Year	Year in which dizziness/vertigo was last documented	Numeric	Ordinal	–
DM-1	Documented DM type 1	Numeric	Nominal	0 = No DM type 1; 1 = DM type 1
DM-1_Year	Year in which DM type 1 was last documented	Numeric	Ordinal	–
DM-2	Documented DM type 2	Numeric	Nominal	0 = No DM type 2; 1 = DM type 2
DM-2_Year	Year in which DM type 2 was last documented	Numeric	Ordinal	–
DM-Retinopathy	Documented DM retinopathy	Numeric	Nominal	0 = No DM retinopathy; 1 = DM retinopathy
DM-Retinopathy_Year	Year in which DM retinopathy was last documented	Numeric	Ordinal	–
DM-Neuropathy	Documented DM neuropathy	Numeric	Nominal	0 = No DM neuropathy; 1 = DM neuropathy
DM-Neuropathy_Year	Year in which DM neuropathy was last documented	Numeric	Ordinal	–
Epilepsy	Documented epilepsy	Numeric	Nominal	0 = No epilepsy; 1 = Epilepsy
Epilepsy_Year	Year in which epilepsy was last documented	Numeric	Ordinal	–
Fall	Documented fall	Numeric	Nominal	0 = No history of fall; 1 = History of fall
Fall_Year	Year in which a fall was last documented	Numeric	Ordinal	–
FearFalling	Documented fear of falling	Numeric	Nominal	0 = No fear of falling; 1 = Fear of falling
FearFalling_Year	Year in which fear of falling was last documented	Numeric	Ordinal	–
Gait-BalanceImp	Documented gait/balance impairment	Numeric	Nominal	0 = No gait/balance impairment; 1 = Gait/balance impairment
Gait-BalanceImp_Year	Year in which gait/balance impairment was last documented	Numeric	Ordinal	–

Hypotension	Documented hypotension	Numeric	Nominal	0 = No hypotension; 1 = Hypotension
Hypotension_Year	Year in which hypotension was last documented	Numeric	Ordinal	–
VisionImp	Documented vision impairment	Numeric	Nominal	0 = No vision impairment; 1 = Vision impairment
VisionImp_Year	Year in which vision impairment was last documented	Numeric	Ordinal	–
Parkinsons	Documented Parkinson’s	Numeric	Nominal	0 = No Parkinson’s; 1 = Parkinson’s
Parkinsons_Year	Year in which Parkinson’s was last documented	Numeric	Ordinal	–
Stumble	Documented stumble	Numeric	Nominal	0 = No stumble; 1 = Stumble
Stumble_Year	Year in which a stumble was last documented	Numeric	Ordinal	–
WalkingAid	Documented use of a walking aid	Numeric	Nominal	0 = No walking aid; 1 = Walking aid
WalkingAid_Year	Year in which use of a walking aid was last documented	Numeric	Ordinal	–
RheumatoidArthritis_Med	Documented active prescription for a rheumatoid arthritis medication	Numeric	Nominal	0 = No rheumatoid arthritis medication; 1 = Rheumatoid arthritis medication
RheumatoidArthritis_Med_Year	Year in which active prescription for a rheumatoid arthritis medication was last documented	Numeric	Ordinal	–
Vertigo_Med	Documented active prescription for a vertigo medication	Numeric	Nominal	0 = No vertigo medication; 1 = Vertigo medication
Vertigo_Med_Year	Year in which active prescription for a rheumatoid vertigo medication was last documented	Numeric	Ordinal	–

Sedative_Med	Documented active prescription for a sedative medication	Numeric	Nominal	0 = No sedative medication; 1 = Sedative medication
Sedative_Med_Year	Year in which active prescription for a sedative medication was last documented	Numeric	Ordinal	–
AntiEpileptic_Med	Documented active prescription for an antiepileptic medication	Numeric	Nominal	0 = No antiepileptic medication; 1 = Antiepileptic medication
AntiEpileptic_Med_Year	Year in which active prescription for an antiepileptic medication was last documented	Numeric	Ordinal	–
AntiHTN_Med	Documented active prescription for an antihypertensive medication	Numeric	Nominal	0 = No antihypertensive medication; 1 = Antihypertensive medication
AntiHTN_Med_Year	Year in which active prescription for an antihypertensive medication was last documented	Numeric	Ordinal	–
Dementia_Med	Documented active prescription for a dementia medication	Numeric	Nominal	0 = No dementia medication; 1 = Dementia medication
Dementia_Med_Year	Year in which active prescription for a dementia medication was last documented	Numeric	Ordinal	–
DM-1_Med	Documented active prescription for a DM type 1 medication	Numeric	Nominal	0 = No DM type 1 medication; 1 = DM type 1 medication
DM-1_Med_Year	Year in which active prescription for a DM type 1 medication was last documented	Numeric	Ordinal	–
DM-2_Med	Documented active prescription for a DM type 2 medication	Numeric	Nominal	0 = No DM type 2 medication; 1 = DM type 2 medication

DM-2_Med_Year	Year in which active prescription for a DM type 2 medication was last documented	Numeric	Ordinal	–
Epilepsy_Med	Documented active prescription for an epilepsy medication	Numeric	Nominal	0 = No epilepsy medication; 1 = Epilepsy medication
Epilepsy_Med_Year	Year in which active prescription for an epilepsy medication was last documented	Numeric	Ordinal	–
Hypotension_Med	Documented active prescription for a hypotension medication	Numeric	Nominal	0 = No hypotension medication; 1 = Hypotension medication
Hypotension_Med_Year	Year in which active prescription for a hypotension medication was last documented	Numeric	Ordinal	–
Osteoporosis_Med	Documented active prescription for an osteoporosis medication	Numeric	Nominal	0 = No osteoporosis medication; 1 = Osteoporosis medication
Osteoporosis_Med_Year	Year in which active prescription for an osteoporosis medication was last documented	Numeric	Ordinal	–
Parkinsons_Med	Documented active prescription for a Parkinson’s medication	Numeric	Nominal	0 = No Parkinson’s medication; 1 = Parkinson’s medication
Parkinsons_Med_Year	Year in which active prescription for a Parkinson’s medication was last documented	Numeric	Ordinal	–
Height	Last recorded patient height (in inches)	Numeric	Continuous	–
Height_Year	Last year in which patient height was recorded	Numeric	Ordinal	–

Height_DaysDiff	Time interval in days between date of first visit and date of last documentation of patient height	Numeric	Ordinal	–
Weight	Last recorded patient weight (in pounds)	Numeric	Continuous	–
Weight_Year	Last year in which patient weight was recorded	Numeric	Ordinal	–
Weight_DaysDiff	Time interval in days between date of first visit and date of last documentation of patient weight	Numeric	Ordinal	–
BMI	Last calculated patient body mass index	Numeric	Continuous	–
BMI_Year	Last year in which patient body mass index was calculated	Numeric	Ordinal	–
BMI_DaysDiff	Time interval in days between date of first visit and date of last calculation of patient body mass index	Numeric	Ordinal	–
Systolic	Last documented systolic blood pressure reading	Numeric	Continuous	–
Systolic_Year	Last year in which systolic blood pressure reading was documented	Numeric	Ordinal	–
Systolic_DaysDiff	Time interval in days between date of first visit and date of last documentation of systolic blood pressure reading	Numeric	Ordinal	–
Diastolic	Last documented diastolic blood pressure reading	Numeric	Continuous	–
Diastolic_Year	Last year in which diastolic blood pressure reading was documented	Numeric	Ordinal	–
Diastolic_DaysDiff	Time interval in days between date of first visit and date of last documentation of diastolic blood pressure reading	Numeric	Ordinal	–

Age_Cat_1	Recoded age, using 65–84 and 85+ age ranges	Character	Nominal	–
Age_Cat_2	Recoded age, using 65–74, 75–84, and 85+ age ranges	Character	Nominal	–
BMI_Cat_1	Recoded body mass index, using <30 and ≥30 (obese) ranges	Character	Nominal	0 = <30; 1 = ≥30
Closest_BMI	BMI measurement closest to the date of last documented fall. If no fall, then result = latest BMI	Numeric	Continuous	–
Closest_Systolic	Systolic blood pressure reading closest to the date of last documented fall. If no fall, then result = latest systolic reading	Numeric	Continuous	–
Closest_Diastolic	Diastolic blood pressure reading closest to the date of last documented fall. If no fall, then result = latest diastolic reading	Numeric	Continuous	–

Abbreviations: BMI, body mass index; DM, diabetes mellitus.