National Institute for Health and Care Excellence

Draft for consultation

# Falls: assessment and prevention in older people and people 50 and over at higher risk (update)

## Evidence review D: Electronic patient records

*NICE guideline <number>*

*Evidence review underpinning recommendations 1.1.1 to 1.1.8 in the NICE guideline*

*October 2024*



*These evidence reviews were developed by NICE*

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# 1. Electronic patient records for identifying people at risk of falls

## 1.1. Review question

How accurate are electronic patient records for identifying people at risk of falls?

### 1.1.1. Introduction

When an individual comes under the care of a medical professional, service or organisation, information is collected in a number of areas including demographics, signs, symptoms, test results, diagnoses, prescriptions, operations, test results, referrals, dates of admission and discharge. This is digitally stored in the form of an electronic patient record. Given that the risk of falling and fall-related injuries is associated with a number of different factors or causes it would appear plausible that reviewing the data held on a patient population would identify those patients at increased risk of falling and where further clinical assessment would be beneficial.

The electronic frailty index (eFI) uses electronic primary care patient records to identify populations of older people who may be living with varying degrees of frailty. The eFI uses a 'cumulative' deficit model measuring frailty on the basis of the accumulation of 36 different deficits including signs, symptoms, diseases and disabilities. All general practices in England are required to use the eFI or a similar tool to identify patients identified as living with moderate or severe frailty. Patients living with high frailty should be offered an annual medicines review and falls risk assessment where clinically appropriate. Patients living with moderate frailty should be considered for an annual medicines review and falls risk assessment where clinically appropriate.

Electronic patient records can be searched for relevant codes or terms by individuals or using specific programs. The use of 'artificial intelligence' in searching electronic patient records for predictive purposes is an emerging and rapidly developing area. This involves Foundation Models (FMs) which are machine learning models initially trained on very large datasets and then able to perform different tasks with minimal training specific to the task. Numerous FMs have been developed that have been trained on electronic patient records.

### 1.1.2. Summary of the protocol

For full details see the review protocol in Appendix A.

**Table 1: PICO characteristics of review question**

| | |
|---|---|
| **Population** | Inclusion:<br>• people aged 65 and over<br>• people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling.<br>It was identified that there are some people aged younger than 65 who have an increased risk of falling, such as those with Parkinson's disease or diabetes.<br><br>Exclusion:<br>• people under 65, and people with a condition or conditions that may put them at increased risk of falling under the age of 50. |

| | |
|---|---|
| | Strata: age group: people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling; settings (hospitals, community, long-term residential care) |
| **Prediction risk tool** | Electronic patient record database used to identify patients at risk of falls.<br>• Identification of those at risk through specific searches<br>• Automatic identification of those at risk<br>Strata: age group: people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling; settings (hospitals, community, long-term residential care). A younger age group may be at less risk than those who are older, so this has been stratified. The different settings would use different record systems. Community would be mainly based on primary care records; care homes could use the care records held in home +/- primary care records. Also the populations behave very differently in fall prevention interventions. i.e. what works in community dwellers is not effective in hospital. Therefore, would anticipate this finding if looking for the effectiveness of electronic record searches. |
| **Condition/ domain being studied** | Falls |
| **Outcomes** | Accuracy of estimation of risk of falls:<br>• Discrimination (sensitivity, specificity, predictive values)<br>• Area under the ROC curve (c-statistic, c-index)<br>• Predicted risk versus observed risk (calibration)<br>• Reclassification<br>Other statistical measures for example: D statistic, $R^2$ statistic and Brier points |
| **Study design** | Internal or external validation studies (prospective or retrospective cohort studies or systematic reviews of these).<br>External validation studies (tested on a different study sample to the derivation sample) are preferred, although internal derivation studies (where the validation sample are different, but still drawn from the identical population to the derivation sample) will also be included.<br>Published NMAs and IPDs will be considered for inclusion.<br>Exclusion:<br>• Case-control studies<br>• Cross-sectional studies |

### 1.1.3. Methods and process

This evidence review was developed using the methods and process described in Developing NICE guidelines: the manual. Methods specific to this review question are described in the review protocol in appendix A and the methods document.

Declarations of interest were recorded according to NICE's conflicts of interest policy.

### 1.1.4. Risk prediction evidence

Evidence was identified regarding various models which incorporate data from electronic health records to identify people at risk of falls. The models and the specified outcomes are summarised in Table 2. Full details can be found in Appendix D.

#### 1.1.4.1. Included studies

Eleven cohort studies were included in this review. One study combined a frailty index with electronic health records, and ten studies incorporated the use of a machine learning or other similar type of algorithm.[1-7, 9-12] 8 studies (Chu, 2022[2], Dormosh, 2022a[6], Dormosh, 2023a[5], Dormosh, 2023b[3], Marier, 2016[7], Pajewski, 2019[9], Patterson, 2019[10], Thapa, 2022[11]) were primary multivariare prognostic studies and 3 studies (Archer, 2024[1] Dormosh, 2022b[4] and Ye, 2020[12]) were clinical prediction models tested in an independent population sample.

These are summarised in Table 2. Studies with populations aged sixty-five years or older, or between the ages of fifty to sixty-four years with a condition which may increase their risk of falling were included. Participants from a range of settings including hospital, community, or long-term residential care were included. Evidence from these studies is summarised in the clinical evidence summary below.

See also the study selection flow chart in Appendix Cand study evidence tables in Appendix D.

#### 1.1.4.2. Excluded studies

No Cochrane reviews were identified at the full text screening level.

See the excluded studies list in Appendix J.

### 1.1.5. Summary of studies included in the prognostic evidence

The included study characteristics are summarised in the table below.

**Table 2: Summary of studies included in the evidence review**

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| Archer, 2024[1]<br><br>Retrospective population-based development, internal and validation cohort study using routinely collected data from primary care electronic health records (EHR) data | eFalls prediction model | All individuals aged ≥65 years<br><br>Median age (IQR): 74 years (69, 81)<br><br>Sex: 54% female<br><br>Setting: Community GP practices UK | Emergency department (ED) attendance/hospitalisation with fall or fracture (as an indicator of a fall injury) within 1 year of assessment in general practice | Fallers: 2389<br><br>Non-Fallers: 79296 |

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| Chu, 2022[2]<br><br>Internal validation using dataset from one hospital | Machine learning algorithms including extreme gradiant boosting (XGBoost), Random Forest, Light gradiant boosting (LightGBM), Deep neural network (DNN), stochastic gradient descent (SGD), and logistic regression<br><br>(n=1101) | Hospitalised elderly participants<br><br>Mean age (SD): 86.08 (NR)<br><br>Sex: 60% female<br><br>Setting: Taichung Veterans General Hospital, Taiwan | Falls risk- no formal definition (the falls were derived from the CGA questionnaire) | Fallers: 349<br><br>Non-Fallers: 752 |
| Dormosh, 2022a[6]<br><br>Retrospective population-based development and internal validation cohort study using routinely collected data from primary care electronic health records (EHR) data<br><br>50 general practices | Free text search algorithm<br><br>(n=36470) | Community-dwelling participants aged 65 years or older<br><br>Mean age (range): 71.74 (68.24 to 77.98).<br><br>Sex: 51.7% female in nonfallers and 63.3% female in fallers<br><br>Setting: 5 municipalities in the Netherlands | Any fall during the 1-year follow-up period | Fallers: 4778<br><br>Non-Fallers: 31692 |
| Dormosh, 2022b[4] | Prediction model using free text search. | Community-dwelling participants | Falls during the 1-year follow-up period | Fallers: 5124<br>Non-Fallers: 33009 |

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| External validation of a model used in Dormosh 2022a using primary care electronic health records (EHR) data<br><br>59 general practices | (n=39,342) | aged 65 years or older<br><br>Mean age (range): 73 (69 to 79) years<br><br>Sex: 56% female<br><br>Setting: 2 cities Amsterdam and Haarlem in North Holland, Netherlands | | The development and validation cohort were in different general practices, so expected little overlap with patients, unless they moved GP. |
| Dormosh, 2023a[5]<br><br>Retrospective population-based development and internal validation cohort study using text searching of electronic patient records unstructed clinical notes. | Natural language processing of unstructured clinical data from electronic health records - Topic-based model<br><br>Natural language processing of unstructured clinical data from electronic health records - Combi model<br><br>Natural language processing of unstructured clinical data from electronic health records - Baseline model | Primary care EHR data of people aged 65 or over.<br><br>Mean age (range): 71.4 (68 to 77)<br><br>Sex: 55% female<br><br>Setting: community in North Holland, Netherlands | The outcome was defined as any fall event that occurred in the 1-year follow-up period and was ascertained by a manual chart review of the clinical notes associated with patients in the follow-up period. | Fallers: = 4,778<br><br>Non-Fallers: = 31,692 |
| Dormosh, 2023b[3]<br><br>Retrospective population- | Prognostic prediction model for inpatient falls using EHR data | Patients admitted to a tertiary care hospital aged 70 years or older who did | The outcome was the occurrence of any inpatient fall after 24 hours of hospital | Fallers: 470<br><br>Non-Fallers: 20,816 |

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| based development and internal validation cohort study using routinely collected data from primary care electronic health records (EHR) data | of a large hospital. | not experience falls during the first 24 hours of admission.<br><br>Median age (IQR): 73 (72, 81)<br><br>Sex: 47.1% female<br><br>Setting: hospital setting in Amsterdam | admission and during the hospital stay, regardless whether the patient fell multiple times or not. | |
| Marier, 2016[7]<br><br>Internal validation cohort study of electronic medical record system<br><br>13 Nursing homes. | Models using the minimum data set (MDS) assessments alone, MDS assessments and electronic medical record (EMR) data alone, MDS assessments and EMR duplicates, or MDS assessments, EMR data alone and EMR duplicates combined (n=5129) | Nursing home residents<br><br>Mean age (SD): NR<br><br>Sex: NR<br><br>Setting: for-profit nursing home, California, USA. | Fall risk | 32.3% of observed falls were identified with EMR data.<br><br>28.6% observed falls were identified with information from the minimum data set (MDS), a standardised screening and assessment tool for residents in a Medicare and/or Medicaid-certified nursing homes in the United States. |
| Pajewski, 2019[9]<br><br>Electronic frailty index using data from the electronic health record | Electronic health record frailty index (eFI) (n=12,798) | Patients aged 65 years or older enrolled in Medicare<br><br>Mean age (SD): 75 (7.3)<br><br>Sex: 57.6% female<br><br>Setting: USA | Injurious falls-according to ICD-10 codes and linked with an emergency department visit | 9013 patients had sufficient health data to calculate eFI. |

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| Patterson, 2019[10]<br><br>Retrospective observational study using automated system using Electronic health records.<br><br>One single academic medical centre ED with level 1 trauma centre | Machine learning platforms including Random forest, AdaBoost, and regression-based models (including linear regression, ridge logistic regression, lasso logistic regression, and logistic regression) (n=10,030 records) | Patients aged 65 years or older who visited the emergency department<br><br>Mean age (SD): 76 (8.4) years<br><br>Sex: 60.5% women<br><br>Setting: USA | Falls risk | 857 patients returned to the hospital within 6 months for a falls-related visit. |
| Thapa, 2022[11]<br><br>Retrospecive study using EHR data in skilled nursing facilities | Machine learning platforms: XGBoost, Logistic Regression, and Multilayered perceptron (n=2785) | Older adults in senior care facilities (60 years and older)<br><br>Mean age (SD): NR but most participants were 80-100 age range.<br><br>Sex: 65% female non-fallers; 66% female fallers<br><br>Setting: USA | Fall risk at 3 months | 153 residents fell within 3 months. |
| Ye, 2020[12]<br><br>External validation cohort using EHR data across the state of Maine (35 hospitals, 34 health centres). | Machine learning algorithm developed from XGBoost, Support Vector Machine (SVM), K-nearest neighbors (KNN), Lasso, | Patients aged 65 years or older who visited health care facilities in Maine<br><br>Mean age (SD): 74.7 (12)<br><br>Sex:55.4% female | Fall prediction and model validation | The model captured 58.01% of falls that happened within 30 days of the next year and 54.93% of falls that happened within 30-60 days of the next year. |

| Study | Risk tool | Population | Outcomes (including definitions) | Estimation of fall risk |
|---|---|---|---|---|
| | and Random Forest. | Setting: Maine, USA | | |

1 See Appendix D for full evidence tables

2 **Table 3: Listed predictors of studies**

| Study | Predictors |
|---|---|
| Archer, 2024[1] | Age (years), Polypharmacy, Gender, BMI category ,Smoking, Alcohol consumption, Abdominal pain, Activity limitation , Anaemia and haematinic deficiency Asthma, Atrial fibrillation, Back pain, Bone disease, Cancer, Cognitive impairment, COPD , Dementia Depression, Diabetes mellitus, Dizziness, Dressing and grooming problems, Faecal incontinence, Falls, Fatigue, Foot problems Fracture, Fragility fracture, General mental health, Headache, Hearing impairment, Heart failure, Housebound, Hypertension, Hypotension or syncope, Inflammatory arthritis, Inflammatory bowel disease, Liver problems, Meal preparation problems Medication management, Memory concerns, Mobility problems, Mono or hemiparesis, Motor neurone disease, Musculoskeletal problems, Osteoarthritis, Osteoporosis, Palliative care, Parkinsonism and tremor, Peptic ulcer disease, Peripheral neuropathy, Peripheral vascular disease, Requirement for care, Respiratory disease, Seizures, Self-harm, Severe mental illness, Skin ulcer, Sleep problems, Social vulnerability, Stress, Stroke, Thyroid problems, Urinary incontinence, Urinary system disease, Visual impairment, Washing and bathing, Weakness, Weight loss. |
| Dormosh, 2022a[6] | A total of 79 predictors known to be associated with falls were included. Demographic predictors included age in years (at the beginning of the observational period) and sex. Medication predictors used were coded using the Anatomical Therapeutic Chemical (ATC) classification system. The International Classification of Primary Care (ICPC) is the standard for coding and classification of complaints, symptoms, and disorders in general practice in the Netherlands. ICPC codes were grouped into 43 chronic condition groups according to previous classification and expert knowledge. Predictors identified in the final prediction model for future falls included age, female sex, history of falls, use |

| Study | Predictors |
|---|---|
| | of proton pump inhibitors, use of opioids, previous injury, depression, osteoarthritis, urinary incontinence, and memory and concentration problems. |
| Dormosh, 2022b[4] | 10 predictors including age, sex, proton pump inhibitors, opioids, previous injury, depression, osteoarthritis, urinary incontinence, memory and concentration problems, and history of falls. |
| Dormosh 2023b[3] | 66 potential predictors for inpatient falls. These predictors can be classified into 7 categories.<br><br>Demographic predictors, Fall history, Health care utilization, Physiologic predictors, Biochemical predictors, Comorbidity predictors, Medication predictors, Patient risk assessment scores. |
| Marier, 2016[7] | A prior fall in the last 6 months, full ambulation, wheelchair use, use of walking aids, an unsteady gait or imbalance, wandering, osteoporosis, anemia, epilepsy, use of antianxiety, antipsychotic, or antidepressant medications, and dementia. |
| Patterson, 2019[10] | Age, vital signs during the index ED visit, duration of the index visit, and number of primary care or hospital visits in the six months prior to the index visit |
| Pajewski, 2019[9] | Diagnosis codes including: anemia, rheumatoid arthritis or osteoarthritis, atrial fibrillation, stroke or transient ischemic attack, renal disease, diabetes, dizziness or vertigo, dyspnoea, falls, fragility or fracture, hearing impairment, congestive heart failure, valvular disease, hypertension (uncomplicated and complicated), hypotension/ syncope, myocardial infarction, coronary atherosclerosis and other heart disease, melanoma, blood-related cancer, cancer (excluding melanoma, blood-related or skin cancer), dementia, osteoporosis, Parkinson's disease, peptic ulcer, peripheral vascular disease, pulmonary disease, skin ulcer, thyroid disease, urinary incontinence, urinary system disease, blindness and other vision defects, weight loss, depression, mild liver disease, moderate or severe liver disease, and chronic pain.<br><br>Laboratory measures and vital signs including: obesity (body mass index), underweight (body mass index), systolic blood pressure (BP), diastolic blood pressure (BP), eGFR (CKD-EPI equation), HDL cholesterol, total cholesterol, triglycerides, potassium, sodium, aspartate |

| Study | Predictors |
|---|---|
| | aminotransferase (SGOT), mean corpuscular volume, blood urea nitrogen, calcium, albumin, total protein, alkaline phosphatase, hemoglobin, and glucose.<br><br>Functional data including: smoking, polypharmacy, activities of daily living, instrumental activities of daily living, self-reported health status, can perform rise from a chair without using arms, diagnosis of dementia or cognitive impairment, hearing concerns or use of hearing aid, overall stress level (does stress affect daily life), and typical amount of pain (does pain affect daily life). |
| Thapa, 2022[11] | Biological (respiratory rate, diastolic blood pressure, systolic blood pressure, heart rate, temperature), biochemical (glucose, CO2, sodium, creatinine, potassium, calcium, chloride, blood urea nitrogen, albumin, cholesterol), demographics (age, sex), physical (height, weight, lower extremity fracture or dislocation, history of fall), comorbidities (chronic kidney disease, cancer, diabetes, hypertension, chronic heart failure, dementia, chronic obstructive pulmonary disease, myocardial infarction, arrhythmia, other mental behaviours or disorders, schizophrenia or psychosis, mood or affective disorders or somatoform, movement disorder, lower extremity fracture, vertebrae and neck fracture, healed fractures, stroke and cerebrovascular, history of all, abnormal gait, weakness, dizziness, and unsteadiness, vertigo), medications (antiepileptic, anticonvulsant, benzodiazepine, antidepressants, narcotics, diuretics, beta blockers, anticholinergics antimuscarinics, antispasmodics, antipsychotics, neuromuscular blocking agents, antihistamines, calcium channels, antiarrhythmics, angiotensin converting enzyme inhibitors, alpha adrenergic blocking agents, sedative hypnotic, number of active medications). |
| Ye, 2020[12] | 157 impactful predictors (top 55 specified in supplemental material) were captured out of a pool of 10,198 predictor candidates.<br><br>Age, female gender, abnormalities of gait and balance, anemia, cognitive disease, gout, urinary disease, cardiovascular disease, muscle disorders, orthostatic hypotension, hypertension, lipid disorders, heart failure, cerebral infarction, Parkinson's disease, epilepsy and recurrent seizures, osteoporosis, abrasion of knee, type 2 diabetes, type 1 diabetes, fall history, |

| Study | Predictors |
| --- | --- |
| | cardiovascular medications (including beta2-adrenergic agnoist, loop diuretic, angiotensin converting enzyme inhibitor, beta-adrenergic blocker, aldosterone antagonist, and thiazide diuretic), mental medications (including atypical antipsychotic, selective serotonin reuptake inhibitor, benzodiazepine, opioid agonist, dopamine-2 receptor antagonist, SNRI, poisoning by narcotics and psychodysleptics, and tricyclic antidepressant), NSAID, antiepileptics, cholinergic muscarinic antagonist, number of emergency visits last year, outpatient visits in the last 12 months, patient's medical costs last year, inpatient length of days last year, number of medications last year, number of distinct medications last year, number of lab tests year, number of distinct lab tests last year, number of diagnoses last year, number of distinct diagnoses last year, hemoglobin, urea nitrogen, MCHC auto, glomerular filtration rate, and natriuretic peptide B. |

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### 1.1.6. Summary of prognostic evidence

**Table 4: Clinical evidence profile- Nursing home setting: Thapa, 2022[11] XGBoost, Logistic Regression,Multilayered perceptron, and Juniper falls risk assessment score**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| XGBoost | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Area under receiver operating curve= 0.846 (0.794-0.894) | VERY LOW |
| XGBoost | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Very Serious imprecision[c] | Sensitivity=0.706 (0.577-0.833) | VERY LOW |
| XGBoost | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision[c] | Specificity= 0.848 (0.809-0.888) | LOW |
| Logistic Regression | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Area under receiver operating curve= 0.711 (0.645-0.773) | VERY LOW |
| Logistic Regression | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Very Serious imprecision[c] | Sensitivity= 0.706 (0.553-0.859) | VERY LOW |
| Logistic Regression | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Specificity= 0.614 (0.560-0.668) | VERY LOW |

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Multilayered perceptron | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Area under receiver operating curve= 0.697 (0.624-0.765) | VERY LOW |
| Multilayered perceptron | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Very Serious imprecision[c] | Sensitivity= 0.706 (0.571-0.833) | VERY LOW |
| Multilayered perceptron | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Specificity= 0.612 (0.566-0.657) | VERY LOW |
| Juniper falls risk assessment score | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | Area under receiver operating curve= 0.621 (0.547-0.693) | VERY LOW |
| Juniper falls risk assessment score | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision[c] | Sensitivity= 0.351 (0.217-0.485) | LOW |
| Juniper falls risk assessment score | 1 | 350, senior living communities | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision[c] | Specificity= 0.883 (0.854-0.911) | LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was identified to be of very serious risk of bias due to predictor assessments being made with knowledge of the outcome. The authors note predictors were preselected for importance, suggesting the outcome was determined with knowledge of predictor information.*
*b) List of predictors provided in Appendix F.1.*
*c) The judgement of precision was based on visual inspection of the confidence intervals of the area under curve across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision was given.*

**Table 5: Clinical evidence profile- nursing home setting: Marier, 2016[7] Electronic medical data model and Minimum data set model**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Proportion of observed falls by projected fall risk decile[d] | Quality |
|---|---|---|---|---|---|---|---|---|
| Model 1- Minimum data set (MDS) assessments only | 1 | 5129, nursing home | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness | Serious imprecision[c] | 1) 0.023<br>2) 0.039<br>3) 0.051<br>4) 0.063<br>5) 0.068<br>6) 0.068<br>7) 0.103<br>8) 0.117<br>9) 0.165<br>10) 0.286<br>AIC: 6733 | VERY LOW |
| Model 2- MDS assessments and electronic medical records (EMR) only | 1 | 5129, nursing home | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness | Serious imprecision[c] | 1) 0.024<br>2) 0.041<br>3) 0.055<br>4) 0.052<br>5) 0.059<br>6) 0.094<br>7) 0.110<br>8) 0.131<br>9) 0.148<br>10) 0.286<br>AIC: 6749 | VERY LOW |
| Model 3- MDS assessments and EMR duplicates | 1 | 5129, nursing home | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness | Serious imprecision[c] | 1) 0.028<br>2) 0.028<br>3) 0.042<br>4) 0.048<br>5) 0.076 | VERY LOW |

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Proportion of observed falls by projected fall risk decile[d] | Quality |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | 6) 0.077<br>7) 0.110<br>8) 0.111<br>9) 0.156<br>10) 0.323<br>AIC: 6614 | |
| Model 4- MDS assessments, EMR only and EMR duplicates | 1 | 5129, nursing home | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness | Serious imprecision[c] | 1) 0.028<br>2) 0.027<br>3) 0.038<br>4) 0.052<br>5) 0.073<br>6) 0.082<br>7) 0.108<br>8) 0.121<br>9) 0.151<br>10) 0.320<br>AIC: 6626 | VERY LOW |

*a) Risk of bias was assessed using the PROBAST checklist. . Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to insufficient reporting of inclusion and exclusion criteria, predictor assessments made with knowledge of the outcome, and limited information regarding outcome reporting.*
*b) A list of predictors is available in Appendix F.2.*
*c) The judgement of precision was based on visual inspection of the confidence intervals of the reported observed values. However, confidence intervals were not reported and primary data not available so unable to calculate imprecision. Downgraded by 2 increments*
*d) The proportion of observed falls for each estimated decile of projected resident fall risk, along with the AIC statistic. The 10th decile includes those with the highest projected fall risk; for all four models, the highest proportions of observed falls occur among those in the highest projected risk decile. The proportion of observed falls occurring within each subsequently lower projected decile then declines relatively smoothly for all four models, with individuals in the lowest projected risk decile accounting for only 2% of observed falls. Lower AIC values represent improved goodness of fit.*

**Table 6: Clinical evidence profile- Hospital setting: Chu, 2022[2] Random Forest, XGBoost, Logistic Regression, Light GBM, DNN, and Stochastic Gradient Descent**

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Random Forest | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity= 69.4% | VERY LOW |
| Random Forest | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 69.4% | VERY LOW |
| Random Forest | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 69.4% | VERY LOW |
| Random Forest | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 73.0% | VERY LOW |
| XGBoost | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity=91.0% | VERY LOW |
| XGBoost | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 26.0% | VERY LOW |
| XGBoost | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 57.0% | VERY LOW |

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| XGBoost | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 73.2% | VERY LOW |
| Logistic Regression | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity=68.5% | VERY LOW |
| Logistic Regression | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 58.5% | VERY LOW |
| Logistic Regression | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 68.5% | VERY LOW |
| Logistic Regression | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 70.2% | VERY LOW |
| Light Gradient Boosting Machine (GBM) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity= 69.4% | VERY LOW |
| Light Gradient Boosting Machine (GBM) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 69.4% | VERY LOW |
| Light Gradient Boosting Machine (GBM) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 69.4% | VERY LOW |

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Light Gradient Boosting Machine (GBM) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 70.7% | VERY LOW |
| Deep neural network (DNN) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity= 13.6% | VERY LOW |
| Deep neural network (DNN) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 35.9% | VERY LOW |
| Deep neural network (DNN) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 35.9% | VERY LOW |
| Deep neural network (DNN) | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 65.6% | VERY LOW |
| Stochastic Gradient Descent | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Sensitivity=53.2% | VERY LOW |
| Stochastic Gradient Descent | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Specificity= 53.2% | VERY LOW |
| Stochastic Gradient Descent | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | AUC micro= 53.2% | VERY LOW |

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Stochastic Gradient Descent | 1 | 1101, hospital geriatric ward | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[b] | Predicitive accuracy= 55.9% | VERY LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to insufficient reporting of the inclusion and exclusion criteria and no standardised definition of the outcome was provided.*
*b) The judgement of precision was intended to be based on visual inspection of the confidence intervals of the sensitivity and specificity information provided. However, confidence intervals were not reported and primary data not available so unable to calculate imprecision. Downgraded by 2 increments.*

**Table 7: Clinical evidence profile- Hospital setting: Ye, 2020[12] Adapted prediction model**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Prediction model adapted from XGBoost, Support Vector Machine (SVM), K-nearest neighbors (KNN), Lasso, and Random Forest. | 1 | 265,225, hospitals and federally qualified health centers | Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | C-statistic= 0.807 | VERY LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of serious risk of bias due to insufficient reporting of outcomes and methods regarding the analysis.*
*b) List of predictors provided in Appendix F.3.*
*c) The judgement of precision was intended to be based on visual inspection of the confidence intervals of the C-statistic. However, confidence intervals were not reported in regards to the C-statistic and primary data not available so unable to calculate imprecision so evidence was downgraded by 2 increments.*

**Table 8: Clinical evidence profile- Hospital setting: Patterson, 2019[10] AdaBoost, Random Forest, Ridge Logistic Regression, LASSO Logistic Regression, Linear Regression, and Logistic Regression**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Random Forest | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.78 (0.74–0.81) | VERY LOW |
| AdaBoost | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.78 (0.74–0.81) | VERY LOW |
| Ridge Logistic Regression | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.77 (0.73–0.80) | VERY LOW |
| LASSO Logistic Regression | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.76 (0.73–0.80) | VERY LOW |
| Linear Regression | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.74 (0.71–0.78) | VERY LOW |
| Logistic Regression | 1 | 9687, hospital emergency department | Very Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.72 (0.68–0.76) | VERY LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to insufficient reporting of a standardised definition of the outcome and predictor knowledge being based on fall predictive value.*
*b) 10 predictors provided in Appendix F.4*
*c) The judgement of precision was based on visual inspection of the confidence intervals of the AUC across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision as given.*

**Table 9: Clinical evidence profile- Hospital setting: Dormosh, 2023b Fall prediction model (Without/With indicators for Missing Values)**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Fall prediction model (Without indicators for Missing Values) | 1 | 21405, hospital | Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.676 (0.645- 0.707) | VERY LOW |
| Fall prediction model (With indicators for Missing Values) | 1 | 21405, hospital | Serious risk of bias[a] | No serious inconsistency | No serious indirectness | Serious imprecision[c] | AUC: 0.695 (0.667- 0.724) | VERY LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to lack of exclusion criteria reported and predictor knowledge being based on history of falls.*
*b) 10 predictors provided in Appendix F.9*
*c) The judgement of precision was based on visual inspection of the confidence intervals of the AUC across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision as given.*

**Table 10: Clinical evidence profile- community setting: Dormosh 2022a[6] Free text search algorithm**

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Median (IQR) | Quality |
|---|---|---|---|---|---|---|---|---|
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | Serious imprecision[d] | Area under the receiver operating curve (ROCAUC)= 0.705 (0.700- 0.714) | VERY LOW |
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | No serious imprecision[d] | Area under precision-recall curve (PRAUC)= 0.290 (0.278- 0.298) | LOW |

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Median (IQR) | Quality |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | |
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | Serious imprecision[d] | Sensitivity= 0.623 (0.593- 0.664) | VERY LOW |
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | Serious imprecision[d] | Specificity = 0.698 (0.665- 0.740) | VERY LOW |
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | No serious imprecision[d] | PPV= 0.238 (0.223- 0.256) | LOW |
| Free text search algorithm | 1 | 36470, community | Serious risk of bias[b] | No serious inconsistency | No serious indirectness | No serious imprecision[d] | Brier score= 0.105 (0.103- 0.108) | LOW |

*a) Indicating this study is a primary study of a related study.*
*b) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of serious risk of bias due to a standardised definition not being provided regarding the outcome.*
c) 79 Predictors listed in Appendix F.5.
*d) The judgement of precision was based on visual inspection of the confidence intervals of the ROCAUC across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision as given.*

**Table 11: Clinical evidence profile- community setting: Dormosh 2022b[4] Free text algorithm model**

| Risk tool[c] | No of studies | N, | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Free text algorithm model | 1 | 38133, community | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision[d] | ROCAUC= 0.690 (0.686- 0.698) | LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to insufficient reporting of predictors and prior knowledge of predictors from the previous study.*
*b) Secondary study related to Dormosh 2022a[6]*
*c) 10 predictors provided in Appendix F.6*
*d) The judgement of precision was based on visual inspection of the confidence intervals of the ROCAUC across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision as given.*

**Table 12: Clinical evidence profile- community setting: Dormosh 2023a Natural language processing of unstructured clinical data**

| Risk tool | No of studies | N, | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Natural language processing of unstructured clinical data from electronic health records - Topic-based model | 1 | 35357, community | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision | AUC = 0.685 (0.676–0.694) | LOW |
| Natural language processing of unstructured clinical data from electronic health records - Combi model | 1 | 35357, community | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision | AUC = 0.718 (0.708–0.727) | LOW |

| Risk tool | No of studies | N, | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Natural language processing of unstructured clinical data from electronic health records - Baseline model | 1 | 35357, community | Very serious risk of bias[a] | No serious inconsistency | No serious indirectness | No serious imprecision | AUC: 0.709 (0.700–0.719) | LOW |

*a) Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to insufficient reporting of predictors and prior knowledge of predictors from the previous study.*

**Table 13: Clinical evidence profile- community setting: Archer 2024 eFalls prediction model**

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Mean (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model (cut off 0.10) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Very serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.66 (0.46- 0.82)<br>Specificity = 0.82 (0.79- 0.84) | VERY LOW |
| eFalls prediction model (cut off 0.11) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Very serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.60 (0.41- 0.77)<br>Specificity = 0.84 (0.82- 0.86) | VERY LOW |
| eFalls prediction model (cut off 0.12) | 1 | Per 1000 (81685, community – external | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Very serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.57 (0.37- 0.75)<br>Specificity = 0.86 (0.84- 0.88) | VERY LOW |

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Mean (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| | | validation cohort) | | | | | | |
| eFalls prediction model (cut off 0.13) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Very serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.53 (0.34- 0.72)<br>Specificity = 0.88 (0.86- 0.90) | VERY LOW |
| eFalls prediction model (cut off 0.14) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.48 (0.29- 0.67)<br>Specificity = 0.89 (0.87- 0.91) | VERY LOW |
| eFalls prediction model (cut off 0.15) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.45 (0.26- 0.64)<br>Specificity = 0.91 (0.89- 0.93) | VERY LOW |
| eFalls prediction model (cut off 0.16) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious<br><br>No serious imprecision | Sensitivity= 0.41 (0.24- 0.61)<br>Specificity = 0.92 (0.90- 0.94) | VERY LOW |
| eFalls prediction model (cut off 0.17) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious imprecision[d]<br>No serious imprecision | Sensitivity= 0.38 (0.21- 0.58)<br>Specificity = 0.93 (0.91- 0.95) | VERY LOW |

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Mean (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model (cut off 0.18) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.34 (0.18- 0.54)<br>Specificity = 0.93 (0.91- 0.95) | VERY LOW |
| eFalls prediction model (cut off 0.19) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | Serious imprecision[d]<br><br>No serious imprecision | Sensitivity= 0.32 (0.16- 0.52)<br>Specificity = 0.94 (0.92- 0.95) | VERY LOW |
| eFalls prediction model (cut off 0.20) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision<br><br>No serious imprecision | Sensitivity= 0.30 (0.15- 0.49)<br>Specificity = 0.95 (0.93- 0.96) | LOW |
| eFalls prediction model (cut off 0.21) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision<br><br>No serious imprecision | Sensitivity= 0.27 (0.12- 0.46)<br>Specificity = 0.95 (0.95- 0.96) | LOW |
| eFalls prediction model (cut off 0.22) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision<br><br>No serious imprecision | Sensitivity= 0.25 (0.11- 0.45)<br>Specificity = 0.95 (0.95- 0.97) | LOW |
| eFalls prediction model (cut off 0.23) | 1 | Per 1000 (81685, community | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision | Sensitivity= 0.23 (0.10- 0.42)<br>Specificity = 0.96 (0.95- 0.97) | LOW |

| Risk tool[c] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Mean (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| | | – external validation cohort) | | | | No serious imprecision | | |
| eFalls prediction model (cut off 0.24) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision<br><br>No serious imprecision | Sensitivity= 0.21 (0.08- 0.40)<br>Specificity = 0.97 (0.97- 0.98) | LOW |
| eFalls prediction model (cut off 0.25) | 1 | Per 1000 (81685, community – external validation cohort) | Serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision<br><br>No serious imprecision | Sensitivity= 0.19 (0.07- 0.39)<br>Specificity = 0.97 (0.96- 0.98) | LOW |

a) *Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to the outcome being determined alongside information regarding the predictors. The study also indicated insufficient reporting regarding the model evaluation.*
b) *List of predictors in Appendix F.7.*
c) *This study was marked down due to outcome indirectness. The outcome was limited to patients who experienced injurious falls, which could exclude populations who experience non-injurious falls.*
d) *The judgement of precision was based on visual inspection of the confidence intervals of the sensitivity and specificity across two clinical thresholds: 0.5 and 0.7. The threshold of 0.5 marked the boundary between no predictive value better than chance and a predictive value better than chance. The threshold of 0.7 marked the boundary above which the committee might consider recommendations. If the 95% CIs crossed one of these thresholds a rating of serious imprecision was given and if they crossed both of these thresholds a rating of very serious imprecision as given.*

**Table 14: Clinical evidence profile- insurance setting: Pajewski 2019[9] Electronic medical record frailty index (eFI)**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| Electronic medical record frailty index (eFI)- participants with sufficient data | 1 | 9013, Medicare Shared Savings Plan Accountable Care Organization | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness[d] | Serious imprecision[c] | C-statistic= 0.791 | VERY LOW |

a) *Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to the outcome being determined alongside information regarding the predictors. The study also indicated insufficient reporting regarding the model evaluation.*
b) *List of predictors in Appendix F.7.*
c) *The judgement of precision was intended to be based on visual inspection of the confidence intervals of the C-statistic. However, confidence intervals were not reported in regard to the C-statistic and primary data not available so unable to calculate imprecision so evidence was downgraded by 2 increments.*
d) *This study was marked down due to outcome indirectness. The outcome was limited to patients who experienced injurious falls, which could exclude populations who experience non-injurious falls.*

**Table 15: Clinical evidence profile- community setting: Archer 2024[1] eFalls prediction model**

| Risk tool[b] | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Effect size (95% CI) | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model | 1 | 81685, community – external validation cohort | Very serious risk of bias[a] | No serious inconsistency | Serious indirectness[c] | No serious imprecision | C-statistic= 0.82 (0.80 – 0.83) | VERY LOW |

e) *Risk of bias was assessed using the PROBAST checklist. Downgraded by 1 increment if the majority of the evidence was at high risk of bias, and downgraded by 2 increments if the majority of the evidence was at very high risk of bias. The above study was determined to be of very serious risk of bias due to the outcome being determined alongside information regarding the predictors. The study also indicated insufficient reporting regarding the model evaluation.*
f) *List of predictors in Appendix F.7.*

g) *This study was marked down due to outcome indirectness. The outcome was limited to patients who experienced injurious falls, which could exclude populations who experience non-injurious falls.*

### 1.1.7. Calibration

Dormosh 2022b[4] reported calibration statistics to assess the model. In this study, calibration was evaluated using calibration-in-the-large, the calibration slope and a visual inspection of a calibration plot. The authors note calibration-in-the-large was the mean predicted risk among the validation cohort compared to the mean actual risk, with the ideal value being 0. In this study, calibration-in-the-large for the model across the validation cohort was 0.012 (95%CI 0.018- 0.042). The authors provide further specification across the three cohorts, identified as Cohort A, Cohort B, and Cohort C. Cohort A excluded individuals who did not contact a GP during the follow-up period. Cohort B comprised of individuals who lived in Amsterdam, Cohort C was comprised of individuals who lived in Haarlem. Table 11 depicts the calibration-in-the-large by cohort.

**Table 16: Calibration-in-the-large: Dormosh 2022b[4] Free text algorithm model**

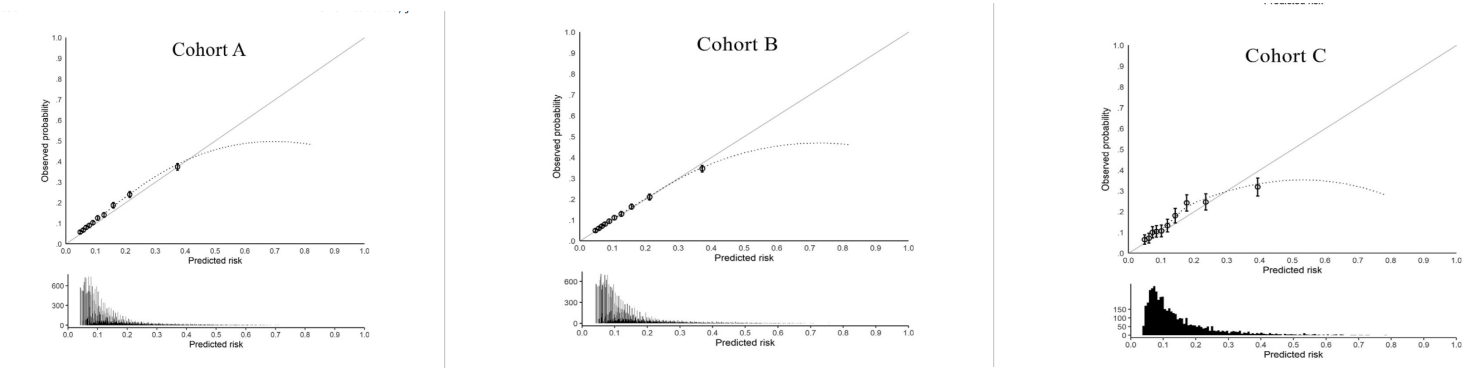
| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Calibration-in-the-large | Quality |
|---|---|---|---|---|---|---|---|---|
| Cohort A | 1 | 35115, community | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | 0.121 | LOW |
| Cohort B | 1 | 33542, community (Amsterdam) | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | -0.002 | LOW |
| Cohort C | 1 | 4591, community (Haarlem) | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | 0.107 | LOW |

Calibration slope is a method used to quantify the correlation between actual and predicted risk across participants, for which, the ideal value is 1. The calibration slope for the model across the validation cohort was 0.878 (95%CI 0.864- 0.915).

**Table 17: Calibration slope: Dormosh 2022b[4] Free text algorithm model**

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Calibration slope | Quality |
|---|---|---|---|---|---|---|---|---|
| Cohort A | 1 | 35115, community | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | 0.912 | LOW |
| Cohort B | 1 | 33542, community (Amsterdam) | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | 0.898 | LOW |
| Cohort C | 1 | 4591, community (Haarlem) | Very serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | 0.735 | LOW |

The calibration plot notes the agreement between predicted risk and actual risk across a range of possibilities. The calibration plot notes a similar trend, however, there was about 5% underestimation of fall risk in Cohort C, with predicted probabilities between 0.15 and 0.25. The calibration plots below depict the sensitivity analysis among specific patient validation cohorts.




Dormosh 2022a[6] provided a calibration plot of the final falls prediction model. The calibration plot provided below demonstrated the relationship between the predicted and observed falls rate.

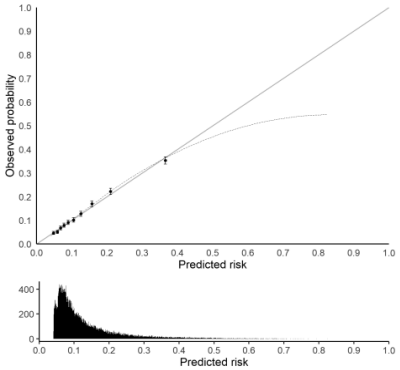


**Table 18: Dormosh 2022a[6]**

| Risk tool | No of studies | n | Risk of bias | Inconsistency | Indirectness | Imprecision | $R^2$ (95%CI) | Brier score (95%CI) | D statistic (95%CI) | Quality |
|---|---|---|---|---|---|---|---|---|---|---|
| Free text search algorithm | 1 | 36470 | Serious risk of bias | No serious inconsistency | No serious indirectness | No serious imprecision | - | 0.105 (0.103-0.108) | - | LOW |

Marier 2016[7] provided a calibration plot identifying the cumulative distribution of observed falls within the validation cohort according to projected risk decile. The calibration plot provided below suggests that in participants identified in lower risk deciles, the models perform similarly. However, as the level of risk increased, Model 1 and Model 2 appear to underperform when compared to Model 3 and Model 4. The noted difference in proportion of observed falls across the used models can be identified as improvement among residents identified to be at a high-risk decile.

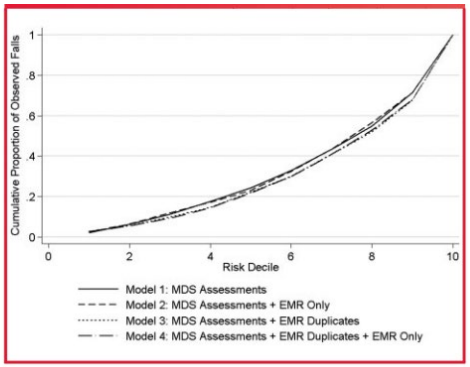


**Table 19: Calibration-in-the-large: Archer 2024[1] eFalls prediction model**

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Calibration-in-the-large | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model | 1 | 81685, community | Very serious risk of bias | No serious inconsistency | Serious indirectness | No serious imprecision | -0.87 (-0.96 to -0.78) | VERY LOW |

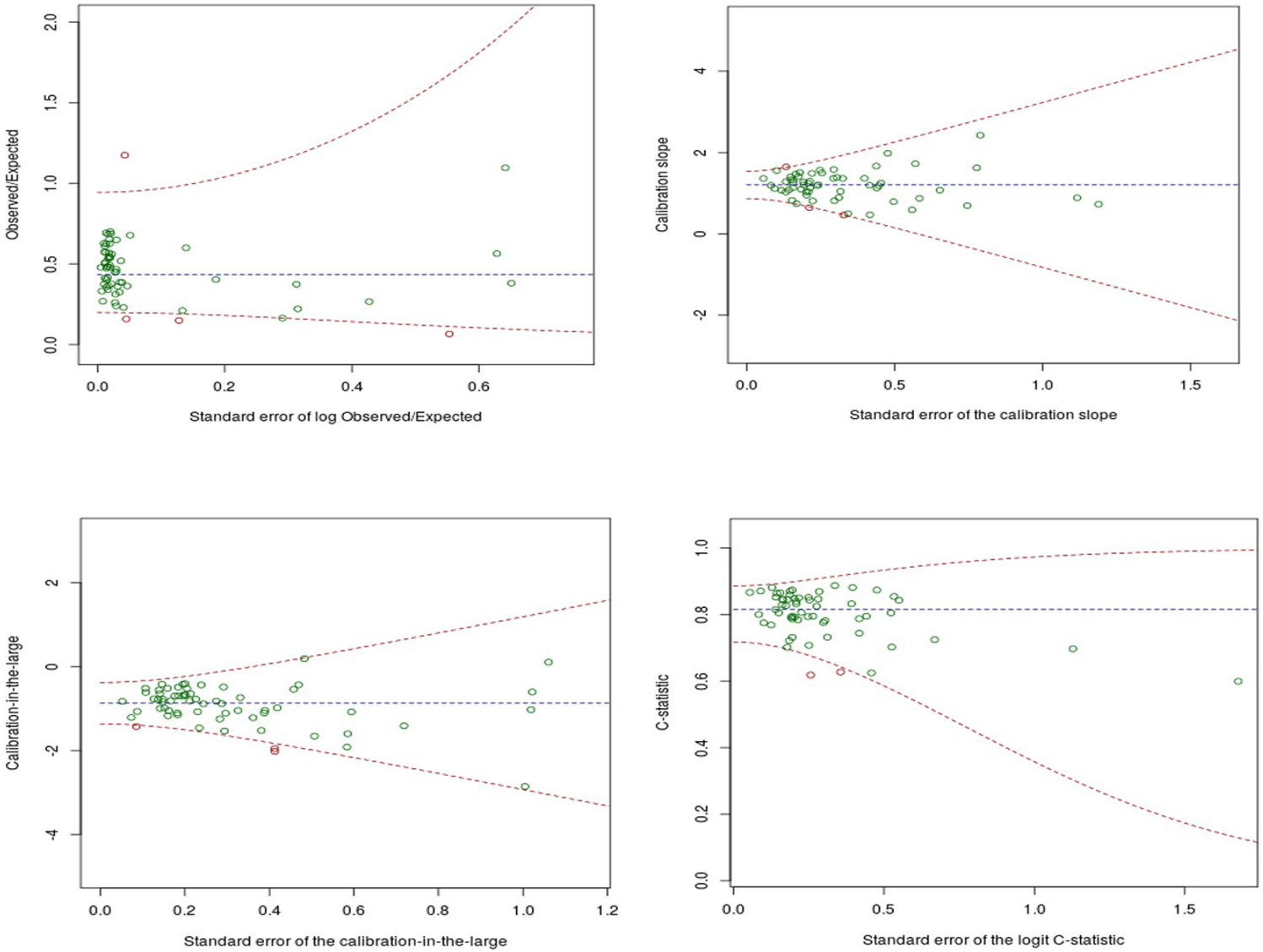
**Table 20: Calibration slope: Archer 2024[1] eFalls prediction model**

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Calibration slope | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model | 1 | 81685, community | Very serious risk of bias | No serious inconsistency | Serious indirectness | No serious imprecision | 1.20 (1.13 to 1.27) | VERY LOW |

**Table 21: Obsevered/expected ratio: Archer 2024[1] eFalls prediction model**

| Risk tool | No of studies | N, setting | Risk of bias | Inconsistency | Indirectness | Imprecision | Obsevered/expected ratio | Quality |
|---|---|---|---|---|---|---|---|---|
| eFalls prediction model | 1 | 81685, community | Very serious risk of bias | No serious inconsistency | Serious indirectness | No serious imprecision | 0.43 (0.38 to 0.48) | VERY LOW |

Archer 2024[1] provided calibration plots showing the variability in performance of the eFalls prediction model on external validation across GP practices—prior to recalibration (see below). Plots show calibration slope, calibration-in-the-large, observed/expected ratio and c-statistic plotted against their standard error within each practice. Bounds show 95% prediction intervals for the performance measure across possible standard errors.



### 1.1.8. Reclassification

None of the included studies provided information regarding reclassification.

### 1.1.9. Economic evidence

#### 1.1.9.1. Included studies

No health economic studies were included.

#### 1.1.9.2. Excluded studies

No relevant health economic studies were excluded due to assessment of limited applicability or methodological limitations.

See also the health economic study selection flow chart in Appendix F.

### 1.1.10. Summary of included economic evidence

No Health Economic studies were included.

### 1.1.11. Economic model

This area was not prioritised for new cost-effectiveness analysis.

### 1.1.12. Evidence statements

#### 1.1.12.1. Effectiveness

#### 1.1.12.2. Economic

No relevant economic evaluations were identified.

### 1.1.13. The committee's discussion and interpretation of the evidence

#### 1.1.13.1. The outcomes that matter most

Due to the limited available evidence, the committee did not prioritise any individual outcomes.

#### 1.1.13.2. The quality of the evidence

The committee noted that the majority of the available evidence was determined to be of low or very low quality according to GRADE.

The committee agreed the evidence was limited. The committee noted that only one study was set in the UK and all others were set in either in the USA, Netherlands or Taiwan so their applicability to an NHS setting may be limited. The committee noted at this time further research in this topic area is needed.

#### 1.1.13.3. Benefits and harms

The committee noted the range of different predictors looked at within the studies included in the review using different systems including machine learning algorithms and free text searching or coding systems. The studies used different predictors, although the committee discussed common predictors used such as age, medication, and history of falls. The

settings of the studies were also very variable from hospital, community and residential nursing homes and the committee agreed the predictors may be different according to the setting due to the availability or importance of the information. For example, studies in hospital settings used predictors such as number of visits to the emergency department and other comorbidities, where as within residential care settings predictors included use of a wheelchair or walking aids, which possibly indicated an older or frailer population. The committee agreed machine learning platforms were still early in development and although the results were of interest further research was needed. They observed that the XGBoost algorithm had a higher sensitivity but this tool had been used within different settings. A recent study by Dormosh 2023 which examined a model using natural language processing of unstructured clinical notes combined with clinical variables, reported AUC data above 70% (the threshold indicating good predictive ability). The same study also assessed a model using only clinical variables (i.e. age, sex, medication groups and chronic medical conditions) which also reported an AUC of over 70%. While, these results are over the 70% threshold of which the committee may consider making a recommendation, it was noted noted that these results are only based on one single study in a primary health care setting in one healthcare system. Clinicians from different settings may have different patterns of clinical documentation, which may impact the generalisability of this model. Consequently, further evidence is needed before this model or similar models could be recommended for use in practice.

The committee were more familiar with the Electronic Record Frailty Index (EFI) which is used to identify frailty risk rather than a risk of falls, from information held within the electronic primary health record. Use of this tool may prompt a falls assessment if frailty is identified. Evidence on the eFalls prediction model, is a recent UK based study by Archer 2024. This tool used 75 predictors and reported good prognostic accuracy with a c-statistic of 0.816 in predicting falls over a 12 month period. Sensitivity and specificity data assessing different cut points of the model were also reported, however, none of the paired values reached the threshold of 0.70 in order for the committee to consider making a recommendation. Additionally, calibration curves showed that the model over-predicted falls risk in the external validation cohort and it should be noted that this model only predicts falls that require an ED attendance. Therefore, further research in different cohorts is needed, before this model or similar models can be recommended for use in practice.

Overall, there is currently not enough evidence to support the use of any of the risk prediction tools, and further evidence is needed within UK health settings to assess the applicability of risk tools in current practice. The committee considered the recommendation not to use falls prediction tools in a hospital setting and agreed with this, but it should be applied to all settings.

#### 1.1.13.4. Cost effectiveness and resource use

No published health economic evidence was identified that met the inclusion criteria. The committee noted that the use of electronic records for flagging people at risk of falls is not commonly done in current practice. One committee member noted that if it is used, then this is more likely to be in hospital settings than in the community. The electronic frailty index tool is commonly used to identify people with frailty using routinely collected primary care data. Those who are identified as being at high risk of frailty may then receive a falls risk assessment, but the purpose of the tool is not to identify people at risk of falls.

Based on the limited clinical evidence and absence of health economic evidence the committee agreed to make no recommendation relating to electronic patient records.

### 1.1.14. Recommendations supported by this evidence review

This evidence review supports recommendations 1.1.1 to 1.1.8 in the NICE guideline.

# References

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3. Dormosh N, Damoiseaux-Volman BA, van der Velde N, Medlock S, Romijn JA, Abu-Hanna A. Development and Internal Validation of a Prediction Model for Falls Using Electronic Health Records in a Hospital Setting. Journal of the American Medical Directors Association. 2023; 24(7):964-970e965

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11. Thapa R, Garikipati A, Shokouhi S, Hurtado M, Barnes G, Hoffman J et al. Predicting Falls in Long-term Care Facilities: Machine Learning Study. JMIR aging. 2022; 5(2):e35373

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# Appendices

## Appendix A Review protocols

### A.1 Review protocol for using electronic patient records for identifying falls in older people

| ID | Field | Content |
|---|---|---|
| 1. | Review title | How accurate are electronic patient records for identifying people at risk of falls? |
| 2. | Review question | Q 2.3 How accurate are electronic patient records for identifying people at risk of falls? |
| 3. | Objective | This review looks at whether the use of electronic patient records, whether by searching or through automatic identification, are accurate at identifying those at risk of falls. |
| 4. | Searches | The following databases (from inception) will be searched:<br>• Embase<br>• MEDLINE<br>• Epistemonikos<br><br>Searches will be restricted by:<br>• English language studies<br>• Human studies |

| | | |
|---|---|---|
| | | The searches may be re-run 6 weeks before the final committee meeting and further studies retrieved for inclusion if relevant.<br><br>The full search strategies will be published in the final review.<br><br>Medline search strategy to be quality assured using the PRESS evidence-based checklist (see methods chapter for full details). |
| 5. | Condition or domain being studied | • Falls: an unexpected event in which the participants come to rest on the ground, floor, or lower level. |
| 6. | Population | Inclusion:<br>• people aged 65 and over<br>• people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling.<br>It was identified that there are some people aged younger than 65 who have an increased risk of falling, such as those with Parkinson's disease or diabetes.<br><br>Exclusion: any age group that does not fit the inclusion criteria.<br><br>Strata: age group: people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling; settings (hospitals, community, long-term residential care) |
| 7. | Prediction risk tool (the electronic patient record is not a tool as such but would identify people at possible risk) | Electronic patient record database used to identify patients at risk of falls. |

| | | |
|---|---|---|
| | | • Identification of those at risk through specific searches<br>• Automatic identification of those at risk<br><br>Strata: age group: people aged 50 to 64 who have a condition or conditions that may put them at higher risk of falling; settings (hospitals, community, long-term residential care).<br><br>A younger age group may be at less risk than those who are older, so this has been stratified.<br>The different settings would use different record systems. Community would be mainly based on primary care records; care homes could use the care records held in home +/- primary care records. Also the populations behave very differently in fall prevention interventions. i.e. what works in community dwellers is not effective in hospital. Therefore, would anticipate this finding if looking for the effectiveness of electronic record searches. |
| 8. | Target condition | • Any fall: an unexpected event in which the participants come to rest on the ground, floor, or lower level. |
| 9. | Types of study to be included | • Internal or external validation studies (prospective or retrospective cohort studies or systematic reviews of these).<br><br>External validation studies (tested on a different study sample to the derivation sample) are preferred, although internal derivation studies (where the validation sample are different, but still drawn from the identical population to the derivation sample) will also be included.<br><br>Published NMAs and IPDs will be considered for inclusion.<br><br>**Exclusion**:<br><br>• Case-control studies<br>• Cross-sectional studies |

| | | |
|---|---|---|
| 10. | Other exclusion criteria | Non-English language studies. |
| 11. | Context | All healthcare settings where electronic patient records are used. |
| 12. | Primary outcomes (critical outcomes) | *All outcomes are considered equally important for decision making and therefore have all been rated as critical:*<br>*Accuracy of estimation of risk of falls:*<br>Statistical outputs may include:<br>• Discrimination (sensitivity, specificity, predictive values)<br>• Area under the ROC curve (c-statistic, c-index)<br>• Predicted risk versus observed risk (calibration)<br>• Reclassification<br>Other statistical measures: for example, D statistic, $R^2$ statistic and Brier points |
| 13. | Data extraction (selection and coding) | EndNote will be used for reference management, sifting, citations and bibliographies.<br>All references identified by the searches and from other sources will be uploaded into EPPI reviewer and de-duplicated.<br>10% of the abstracts will be reviewed by two reviewers, with any disagreements resolved by discussion or, if necessary, a third independent reviewer.<br>The full text of potentially eligible studies will be retrieved and will be assessed in line with the criteria outlined above. |

| | | |
|---|---|---|
| | | A standardised form will be used to extract data from studies (see Developing NICE guidelines: the manual section 6.4).<br><br>10% of all evidence reviews are quality assured by a senior research fellow. This includes checking:<br><br>• papers were included /excluded appropriately<br><br>• a sample of the data extractions<br><br>• correct methods are used to synthesise data<br><br>• a sample of the risk of bias assessments<br><br>Disagreements between the review authors over the risk of bias in particular studies will be resolved by discussion, with involvement of a third review author where necessary.<br><br>Study investigators may be contacted for missing data where time and resources allow. |
| 14. | Risk of bias (quality) assessment | Risk of bias will be assessed using the PROBAST checklist as described in Developing NICE guidelines: the manual. |
| 15. | Strategy for data synthesis | Analyses with and without accounting for competing risks will be included.<br><br>Discrimination, calibration, and re-classification data will be reported separately.<br><br>If appropriate, C statistic and net reclassification index data will be meta-analysed (if at least 3 studies reporting data at the same threshold) in RevMan. Summary outcomes will be reported from the meta-analyses with their 95% confidence intervals in adapted GRADE tables.<br><br>Sensitivity and specificity data will be meta-analysed using a Bayesian approach (using WinBugs software) if 3 or more data points are found.<br><br>Heterogeneity between the studies in effect measures will be assessed using visual inspection of the sensitivity/specificity or net reclassification index RevMan 5 plots, or summary area under the curve (AUC) plots. If data are pooled, |

| | | | |
|---|---|---|---|
| | | an $I^2$ of 50-74% will be deemed serious inconsistency and an $I^2$ of 75% or above very serious inconsistency.<br>If meta-analysis is not possible, data will be presented and quality assessed as individual values in adapted GRADE profile tables and plots of un-pooled sensitivity and specificity from RevMan software.<br>Publication bias will be considered with the guideline committee, and if suspected will be tested for when there are more than 5 studies for that outcome.<br>The risk of bias across all available evidence will be evaluated for each outcome using an adaptation of the 'Grading of Recommendations Assessment, Development and Evaluation (GRADE) toolbox' developed by the international GRADE working group http://www.gradeworkinggroup.org/ | |
| 16. | Analysis of sub-groups | Subgroups that will be investigated if heterogeneity is present: none | |
| 17. | Type and method of review | ☐ | Intervention |
| | | ☐ | Diagnostic |
| | | ☒ | Prognostic |
| | | ☐ | Qualitative |
| | | ☐ | Epidemiologic |
| | | ☐ | Service Delivery |
| | | ☐ | Other (please specify) |
| 18. | Language | English | |
| 19. | Country | England | |
| 20. | Anticipated or actual start date | | |

| | | | | |
|---|---|---|---|---|
| 21. | Anticipated completion date | 21/8/2024 | | |
| 22. | Stage of review at time of this submission | Review stage | Started | Completed |
| | | Preliminary searches | ☑ | ☑ |
| | | Piloting of the study selection process | ☑ | ☑ |
| | | Formal screening of search results against eligibility criteria | ☑ | ☐ |
| | | Data extraction | ☐ | ☐ |
| | | Risk of bias (quality) assessment | ☐ | ☐ |
| | | Data analysis | ☐ | ☐ |
| 23. | Named contact | 5a. Named contact<br>Guideline Development Team NGC<br><br>5b Named contact e-mail<br>Guidelines8@nice.org.uk<br><br>5e Organisational affiliation of the review<br>National Institute for Health and Care Excellence (NICE) | | |
| 24. | Review team members | From NICE:<br>Gill Ritchie [Guideline lead]<br>Julie Neilson [Senior systematic reviewer]<br>Annette Chalker [Systematic reviewer] | | |

| | | |
|---|---|---|
| | | Sophia Kemmis-Betty [Senior Health economist]<br>Steph Armstrong [Health economist]<br>Joseph Runicles [Information specialist]<br>Tamara Diaz [Project manager] |
| 25. | Funding sources/sponsor | Development of this systematic review is being funded by NICE. |
| 26. | Conflicts of interest | All guideline committee members and anyone who has direct input into NICE guidelines (including the evidence review team and expert witnesses) must declare any potential conflicts of interest in line with NICE's code of practice for declaring and dealing with conflicts of interest. Any relevant interests, or changes to interests, will also be declared publicly at the start of each guideline committee meeting. Before each meeting, any potential conflicts of interest will be considered by the guideline committee Chair and a senior member of the development team. Any decisions to exclude a person from all or part of a meeting will be documented. Any changes to a member's declaration of interests will be recorded in the minutes of the meeting. Declarations of interests will be published with the final guideline. |

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## A.2 Health economic review protocol

**Table 22: Health economic review protocol**

| Review question | All questions – health economic evidence |
|---|---|
| **Objectives** | To identify health economic studies relevant to any of the review questions. |
| **Search criteria** | • Populations, interventions and comparators must be as specified in the clinical review protocol above.<br>• Studies must be of a relevant health economic study design (cost–utility analysis, cost-effectiveness analysis, cost–benefit analysis, cost–consequences analysis, comparative cost analysis).<br>• Studies must not be a letter, editorial or commentary, or a review of health economic evaluations. (Recent reviews will be ordered although not reviewed. The bibliographies will be checked for relevant studies, which will then be ordered.)<br>• Unpublished reports will not be considered unless submitted as part of a call for evidence.<br>• Studies must be in English. |
| **Search strategy** | A health economic study search will be undertaken using population-specific terms and a health economic study filter – see appendix B below. |
| **Review strategy** | Studies not meeting any of the search criteria above will be excluded. Studies published before 2007, abstract-only studies and studies from non-OECD countries or the USA will also be excluded.<br>Studies published after 2007 that were included in the previous guideline(s) will be reassessed for inclusion and may be included or selectively excluded based on their relevance to the questions covered in this update and whether more applicable evidence is also identified.<br>Each remaining study will be assessed for applicability and methodological limitations using the NICE economic evaluation checklist which can be found in appendix H of Developing NICE guidelines: the manual (2014).[8]<br><br>**Inclusion and exclusion criteria**<br>• If a study is rated as both 'Directly applicable' and with 'Minor limitations' then it will be included in the guideline. A health economic evidence table will be completed and it will be included in the health economic evidence profile.<br>• If a study is rated as either 'Not applicable' or with 'Very serious limitations' then it will usually be excluded from the guideline. If it is excluded then a health economic evidence table will not be completed and it will not be included in the health economic evidence profile.<br>• If a study is rated as 'Partially applicable', with 'Potentially serious limitations' or both then there is discretion over whether it should be included.<br><br>**Where there is discretion**<br>The health economist will make a decision based on the relative applicability and quality of the available evidence for that question, in discussion with the guideline committee if required. The ultimate aim is to include health economic studies that are helpful for decision-making in the context of the guideline and the current NHS setting. If several studies are considered of sufficiently high applicability and methodological quality that they could all be included, then the health economist, in discussion with the committee if required, may decide to include only the most applicable studies and to selectively exclude the remaining studies. All studies |

| | |
|---|---|
| | excluded on the basis of applicability or methodological limitations will be listed with explanation in the excluded health economic studies appendix below.<br><br>The health economist will be guided by the following hierarchies.<br>*Setting:*<br>• UK NHS (most applicable).<br>• OECD countries with predominantly public health insurance systems (for example, France, Germany, Sweden).<br>• OECD countries with predominantly private health insurance systems (for example, Switzerland).<br>• Studies set in non-OECD countries or in the USA will be excluded before being assessed for applicability and methodological limitations.<br>*Health economic study type:*<br>• Cost–utility analysis (most applicable).<br>• Other type of full economic evaluation (cost–benefit analysis, cost-effectiveness analysis, cost–consequences analysis).<br>• Comparative cost analysis.<br>• Non-comparative cost analyses including cost-of-illness studies will be excluded before being assessed for applicability and methodological limitations.<br>*Year of analysis:*<br>• The more recent the study, the more applicable it will be.<br>• Studies published in 2007 or later (including any such studies included in the previous guideline(s)) but that depend on unit costs and resource data entirely or predominantly from before 2007 will be rated as 'Not applicable'.<br>• Studies published before 2007 (including any such studies included in the previous guideline(s))will be excluded before being assessed for applicability and methodological limitations.<br>*Quality and relevance of effectiveness data used in the health economic analysis:*<br>• The more closely the clinical effectiveness data used in the health economic analysis match with the outcomes of the studies included in the clinical review the more useful the analysis will be for decision-making in the guideline. |

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# Appendix B Literature search strategies

The literature searches for this review are detailed below and complied with the methodology outlined in Developing NICE guidelines: the manual (2014)

For more information, please see the Methodology review published as part of the accompanying documents for this guideline.

### B.1.1 Clinical search literature search strategy

Searches were constructed using a PICO framework where population (P) terms were combined with Intervention (I) and in some cases Comparison (C) terms. Outcomes (O) are rarely used in search strategies as these concepts may not be indexed or described in the title or abstract and are therefore difficult to retrieve. Search filters were applied to the search where appropriate.

**Table 23: Database parameters, filters and limits applied**

| Database | Dates searched | Search filter used |
|---|---|---|
| Medline ALL (OVID) | **01-01-1946 - 07-05-2024** | Systematic reviews<br>Randomised controlled trials<br>Observational studies<br><br>Exclusions (animal studies, letters, comments, editorials, news, historical articles, anecdotes, case studies/reports)<br><br>English language |
| Embase (OVID) | **01-01-1974 - 07-05-2024** | Systematic reviews<br>Randomised controlled trials<br>Observational studies<br><br>Exclusions (animal studies, letters, comments, editorials, case studies/reports, conference abstracts)<br><br>English language |
| The Cochrane Library (Wiley) | Cochrane CENTRAL to 2024 Issue 5 of 12 | |
| HMIC (Ovid) | **01-01-1979 - 07-05-2024** | |
| Epistemonikos (The Epistemonikos Foundation) | No date limits applied (searched 07/05/2024) | |

**Medline (Ovid) search terms**

| | |
|---|---|
| 1 | Accidental Falls/ |
| 2 | (fall or falls or falling or faller* or fallen or fell or slip* or trip* or stumble* or tumble*).ti,ab. |
| 3 | or/1-2 |

| | |
|---|---|
| 4 | letter/ |
| 5 | editorial/ |
| 6 | news/ |
| 7 | exp historical article/ |
| 8 | Anecdotes as Topic/ |
| 9 | comment/ |
| 10 | case report/ |
| 11 | (letter or comment*).ti. |
| 12 | or/4-11 |
| 13 | randomized controlled trial/ or random*.ti,ab. |
| 14 | 12 not 13 |
| 15 | animals/ not humans/ |
| 16 | exp Animals, Laboratory/ |
| 17 | exp Animal Experimentation/ |
| 18 | exp Models, Animal/ |
| 19 | exp Rodentia/ |
| 20 | (rat or rats or mouse or mice or rodent*).ti. |
| 21 | or/14-20 |
| 22 | 3 not 21 |
| 23 | limit 22 to english language |
| 24 | exp Medical Records Systems, Computerized/ or Medical Record Linkage/ |
| 25 | ((electronic or digit* or automat* or computer* or online) adj2 (health or healthcare or medical or patient* or hospital or inpatient* or outpatient*) adj3 (data or record* or information or tool* or identification or database* or portal*)).ti,ab,kf. |
| 26 | ("EMR" or "EPR" or "EHR").ti,ab,kf. |
| 27 | or/24-26 |
| 28 | 23 and 27 |
| 29 | Epidemiologic studies/ |
| 30 | Observational study/ |
| 31 | exp Cohort studies/ |
| 32 | (cohort adj (study or studies or analys* or data)).ti,ab. |

| | |
|---|---|
| 33 | ((follow up or observational or uncontrolled or non randomi#ed or epidemiologic*) adj (study or studies or data)).ti,ab. |
| 34 | ((longitudinal or retrospective or prospective or cross sectional) and (study or studies or review or analys* or cohort* or data)).ti,ab. |
| 35 | Controlled Before-After Studies/ |
| 36 | Historically Controlled Study/ |
| 37 | Interrupted Time Series Analysis/ |
| 38 | (before adj2 after adj2 (study or studies or data)).ti,ab. |
| 39 | exp case control studies/ |
| 40 | case control*.ti,ab. |
| 41 | Cross-sectional studies/ |
| 42 | (cross sectional and (study or studies or review or analys* or cohort* or data)).ti,ab. |
| 43 | or/29-42 |
| 44 | randomized controlled trial.pt. |
| 45 | controlled clinical trial.pt. |
| 46 | randomi#ed.ti,ab. |
| 47 | placebo.ab. |
| 48 | randomly.ti,ab. |
| 49 | Clinical Trials as topic.sh. |
| 50 | trial.ti. |
| 51 | or/44-50 |
| 52 | Meta-Analysis/ |
| 53 | exp Meta-Analysis as Topic/ |
| 54 | (meta analy* or metanaly* or metaanaly* or meta regression).ti,ab. |
| 55 | ((systematic* or evidence*) adj3 (review* or overview*)).ti,ab. |
| 56 | (reference list* or bibliograph* or hand search* or manual search* or relevant journals).ab. |
| 57 | (search strategy or search criteria or systematic search or study selection or data extraction).ab. |
| 58 | (search* adj4 literature).ab. |
| 59 | (medline or pubmed or cochrane or embase or psychlit or psyclit or psychinfo or psycinfo or cinahl or science citation index or bids or cancerlit).ab. |
| 60 | cochrane.jw. |

| | |
|---|---|
| 61 | ((multiple treatment* or indirect or mixed) adj2 comparison*).ti,ab. |
| 62 | or/52-61 |
| 63 | 28 and (51 or 62) |
| 64 | 28 and 43 |
| 65 | 64 not 63 |

**Embase (Ovid) search terms**

| | |
|---|---|
| 1 | falling/ |
| 2 | (fall or falls or falling or faller* or fallen or fell or slip* or trip* or stumble* or tumble*).ti,ab. |
| 3 | or/1-2 |
| 4 | letter.pt. or letter/ |
| 5 | note.pt. |
| 6 | editorial.pt. |
| 7 | case report/ or case study/ |
| 8 | (letter or comment*).ti. |
| 9 | (conference abstract or conference paper).pt. |
| 10 | or/4-9 |
| 11 | randomized controlled trial/ or random*.ti,ab. |
| 12 | 10 not 11 |
| 13 | animal/ not human/ |
| 14 | nonhuman/ |
| 15 | exp Animal Experiment/ |
| 16 | exp Experimental Animal/ |
| 17 | animal model/ |
| 18 | exp Rodent/ |
| 19 | (rat or rats or mouse or mice or rodent*).ti. |
| 20 | or/12-19 |
| 21 | 3 not 20 |
| 22 | limit 21 to english language |

| | |
|---|---|
| 23 | electronic health record/ or electronic medical record/ or electronic patient record/ |
| 24 | ((electronic or digit* or automat* or computer* or online) adj2 (health or healthcare or medical or patient* or hospital or inpatient* or outpatient*) adj3 (data or record* or information or tool* or identification or database* or portal*)).ti,ab,kf. |
| 25 | ("EMR" or "EPR" or "EHR").ti,ab,kf. |
| 26 | or/23-25 |
| 27 | 22 and 26 |
| 28 | Clinical study/ |
| 29 | Observational study/ |
| 30 | family study/ |
| 31 | longitudinal study/ |
| 32 | retrospective study/ |
| 33 | prospective study/ |
| 34 | cohort analysis/ |
| 35 | follow-up/ |
| 36 | cohort*.ti,ab. |
| 37 | 35 and 36 |
| 38 | (cohort adj (study or studies or analys* or data)).ti,ab. |
| 39 | ((follow up or observational or uncontrolled or non randomi#ed or epidemiologic*) adj (study or studies or data)).ti,ab. |
| 40 | ((longitudinal or retrospective or prospective or cross sectional) and (study or studies or review or analys* or cohort* or data)).ti,ab. |
| 41 | (before adj2 after adj2 (study or studies or data)).ti,ab. |
| 42 | exp case control study/ |
| 43 | case control*.ti,ab. |
| 44 | cross-sectional study/ |
| 45 | (cross sectional and (study or studies or review or analys* or cohort* or data)).ti,ab. |
| 46 | or/28-34,37-45 |
| 47 | random*.ti,ab. |
| 48 | factorial*.ti,ab. |
| 49 | (crossover* or cross over*).ti,ab. |
| 50 | ((doubl* or singl*) adj blind*).ti,ab. |
| 51 | (assign* or allocat* or volunteer* or placebo*).ti,ab. |

| | |
|---|---|
| 52 | crossover procedure/ |
| 53 | single blind procedure/ |
| 54 | randomized controlled trial/ |
| 55 | double blind procedure/ |
| 56 | or/47-55 |
| 57 | systematic review/ |
| 58 | meta-analysis/ |
| 59 | (meta analy* or metanaly* or metaanaly* or meta regression).ti,ab. |
| 60 | ((systematic* or evidence*) adj3 (review* or overview*)).ti,ab. |
| 61 | (reference list* or bibliograph* or hand search* or manual search* or relevant journals).ab. |
| 62 | (search strategy or search criteria or systematic search or study selection or data extraction).ab. |
| 63 | (search* adj4 literature).ab. |
| 64 | (medline or pubmed or cochrane or embase or psychlit or psyclit or psychinfo or psycinfo or cinahl or science citation index or bids or cancerlit).ab. |
| 65 | cochrane.jw. |
| 66 | ((multiple treatment* or indirect or mixed) adj2 comparison*).ti,ab. |
| 67 | or/57-66 |
| 68 | 27 and (56 or 67) |
| 69 | 27 and 46 |
| 70 | 69 not 68 |

**Cochrane CENTRAL search terms**

| | |
|---|---|
| #1 | MeSH descriptor: [Accidental Falls] explode all trees |
| #2 | (fall or falls or falling or faller* or fallen or fell or slip* or trip* or stumble* or tumble*):ti,ab |
| #3 | #1 or #2 |
| #4 | MeSH descriptor: [Medical Records Systems, Computerized] explode all trees |
| #5 | MeSH descriptor: [Medical Record Linkage] explode all trees |
| #6 | ((electronic or digit* or automat* or computer* or online) near/2 (health or healthcare or medical or patient* or hospital or inpatient* or outpatient*) near/3 |

| | |
|---|---|
| | (data or record* or information or tool* or identification or database* or portal*)):ti,ab |
| #7 | ("EMR" or "EPR" or "EHR"):ti,ab |
| #8 | #4 or #5 or #6 or #7 |
| #9 | #3 and #8 |

**HMIC search terms**

| | |
|---|---|
| 1 | exp Falling/ |
| 2 | (fall or falls or falling or faller* or fallen or fell or slip* or trip* or stumble* or tumble*).ti,ab. |
| 3 | 1 or 2 |
| 4 | limit 3 to english |
| 5 | exp medical records/ |
| 6 | ((electronic or digit* or automat* or computer* or online) adj2 (health or healthcare or medical or patient* or hospital or inpatient* or outpatient*) adj3 (data or record* or information or tool* or identification or database* or portal*)).ti,ab. |
| 7 | ("EMR" or "EPR" or "EHR").ti,ab. |
| 8 | or/5-7 |
| 9 | 4 and 8 |

**Epistemonikos search terms**

(title:((fall OR falls OR falling OR faller* OR fallen OR fell OR slip* OR trip OR trips OR stumble* OR tumble*)) OR abstract:((fall OR falls OR falling OR faller* OR fallen OR fell OR slip* OR trip* OR stumble* OR tumble*))) AND (title:(("EMR" OR "EPR" OR "EHR" OR electronic medical record* OR electronic patient record* OR electronic health record* OR digital* medical record OR digital* patient record* OR digital health record* OR computer* medical record* OR computer* patient record* OR computer* health record* OR automatic identification)) OR abstract:(("EMR" OR "EPR" OR "EHR" OR electronic medical record* OR electronic patient record* OR electronic health record* OR digital* medical record OR digital* patient record* OR digital health record* OR computer* medical record* OR computer* patient record* OR computer* health record* OR automatic identification)))

## B.2 Health Economics literature search strategy

Health economic evidence was identified by applying economic evaluation and quality of life filters to the clinical literature search strategy in Medline and Embase. The following databases were also searched: NHS Economic Evaluation Database (NHS EED - this ceased to be updated after 31st March 2015), Health Technology Assessment database (HTA - this ceased to be updated from 31st March 2018) and The International Network of Agencies for Health Technology Assessment (INAHTA)

**Table 24: Database parameters, filters and limits applied**

| Database | Dates searched | Search filters and limits applied |
|---|---|---|
| Medline (OVID) | Health Economics<br>1 January 2014 – 8 May 2024 | Health economics studies<br>Quality of Life studies<br><br>Exclusions (animal studies)<br><br>English language |
| | Quality of Life<br>1 January 2004 to – 8 May 2024 | |
| Embase (OVID) | Health Economics<br>1 January 2014 – 8 May 2024 | Health economics studies<br>Quality of Life studies<br><br>Exclusions (animal studies)<br><br>English language |
| | Quality of Life<br>1 January 2004 to – 8 May 2024 | |
| NHS Economic Evaluation Database (NHS EED)<br>(Centre for Research and Dissemination - CRD) | Inception – 31 March 2015 (database no longer updated as of this date) | |
| Health Technology Assessment Database (HTA)<br>(Centre for Research and Dissemination – CRD) | Inception – 31 March 2018 (database no longer updated as of this date) | |
| The International Network of Agencies for Health Technology Assessment (INAHTA) | Inception - 8 May 2024 | English language |

**Medline (Ovid) search terms**

| | |
|---|---|
| 1 | Accidental Falls/ |
| 2 | (fall or falls or falling or faller* or fallen or slip* or trip or trips or tripped or tripping or tumbl*).ti,ab. |
| 3 | or/1-2 |
| 4 | letter/ |
| 5 | editorial/ |

| | |
|---|---|
| 6 | news/ |
| 7 | exp historical article/ |
| 8 | Anecdotes as Topic/ |
| 9 | comment/ |
| 10 | case report/ |
| 11 | (letter or comment*).ti. |
| 12 | or/4-11 |
| 13 | randomized controlled trial/ or random*.ti,ab. |
| 14 | 12 not 13 |
| 15 | animals/ not humans/ |
| 16 | exp Animals, Laboratory/ |
| 17 | exp Animal Experimentation/ |
| 18 | exp Models, Animal/ |
| 19 | exp Rodentia/ |
| 20 | (rat or rats or mouse or mice or rodent*).ti. |
| 21 | or/14-20 |
| 22 | 3 not 21 |
| 23 | limit 22 to english language |
| 24 | limit 23 to yr="2004 -Current" |
| 25 | 23 and 24 |
| 26 | Economics/ |
| 27 | Value of life/ |
| 28 | exp "Costs and Cost Analysis"/ |
| 29 | exp Economics, Hospital/ |
| 30 | exp Economics, Medical/ |
| 31 | Economics, Nursing/ |
| 32 | Economics, Pharmaceutical/ |
| 33 | exp "Fees and Charges"/ |
| 34 | exp Budgets/ |
| 35 | budget*.ti,ab. |
| 36 | cost*.ti. |
| 37 | (economic* or pharmaco?economic*).ti. |
| 38 | (price* or pricing*).ti,ab. |

| | |
|---|---|
| 39 | (cost* adj2 (effective* or utilit* or benefit* or minimi* or unit* or estimat* or variable*)).ab. |
| 40 | (financ* or fee or fees).ti,ab. |
| 41 | (value adj2 (money or monetary)).ti,ab. |
| 42 | or/26-41 |
| 43 | quality-adjusted life years/ |
| 44 | sickness impact profile/ |
| 45 | (quality adj2 (wellbeing or well being)).ti,ab. |
| 46 | sickness impact profile.ti,ab. |
| 47 | disability adjusted life.ti,ab. |
| 48 | (qal* or qtime* or qwb* or daly*).ti,ab. |
| 49 | (euroqol* or eq5d* or eq 5*).ti,ab. |
| 50 | (qol* or hql* or hqol* or h qol* or hrqol* or hr qol*).ti,ab. |
| 51 | (health utility* or utility score* or disutilit* or utility value*).ti,ab. |
| 52 | (hui or hui1 or hui2 or hui3).ti,ab. |
| 53 | (health* year* equivalent* or hye or hyes).ti,ab. |
| 54 | discrete choice*.ti,ab. |
| 55 | rosser.ti,ab. |
| 56 | (willingness to pay or time tradeoff or time trade off or tto or standard gamble*).ti,ab. |
| 57 | (sf36* or sf 36* or short form 36* or shortform 36* or shortform36*).ti,ab. |
| 58 | (sf20 or sf 20 or short form 20 or shortform 20 or shortform20).ti,ab. |
| 59 | (sf12* or sf 12* or short form 12* or shortform 12* or shortform12*).ti,ab. |
| 60 | (sf8* or sf 8* or short form 8* or shortform 8* or shortform8*).ti,ab. |
| 61 | (sf6* or sf 6* or short form 6* or shortform 6* or shortform6*).ti,ab. |
| 62 | or/43-61 |
| 63 | 25 and 42 |
| 64 | limit 63 to yr="2014 -Current" |
| 65 | 25 and 62 |

**Embase (Ovid) search terms**

| | |
|---|---|
| 1 | falling/ |
| 2 | (fall or falls or falling or faller* or fallen or slip* or trip or trips or tripped or tripping or tumbl*).ti,ab. |
| 3 | or/1-2 |

| | |
|---|---|
| 4 | letter.pt. or letter/ |
| 5 | note.pt. |
| 6 | editorial.pt. |
| 7 | case report/ or case study/ |
| 8 | (letter or comment*).ti. |
| 9 | (conference abstract or conference paper).pt. |
| 10 | or/4-9 |
| 11 | randomized controlled trial/ or random*.ti,ab. |
| 12 | 10 not 11 |
| 13 | animal/ not human/ |
| 14 | nonhuman/ |
| 15 | exp Animal Experiment/ |
| 16 | exp Experimental Animal/ |
| 17 | animal model/ |
| 18 | exp Rodent/ |
| 19 | (rat or rats or mouse or mice or rodent*).ti. |
| 20 | or/12-19 |
| 21 | 3 not 20 |
| 22 | limit 21 to english language |
| 23 | limit 22 to yr="2004 -Current" |
| 24 | health economics/ |
| 25 | exp economic evaluation/ |
| 26 | exp health care cost/ |
| 27 | exp fee/ |
| 28 | budget/ |
| 29 | funding/ |
| 30 | budget*.ti,ab. |
| 31 | cost*.ti. |
| 32 | (economic* or pharmaco?economic*).ti. |
| 33 | (price* or pricing*).ti,ab. |
| 34 | (cost* adj2 (effective* or utilit* or benefit* or minimi* or unit* or estimat* or variable*)).ab. |
| 35 | (financ* or fee or fees).ti,ab. |
| 36 | (value adj2 (money or monetary)).ti,ab. |

| | |
|---|---|
| 37 | or/24-36 |
| 38 | quality adjusted life year/ |
| 39 | "quality of life index"/ |
| 40 | short form 12/ or short form 20/ or short form 36/ or short form 8/ |
| 41 | sickness impact profile/ |
| 42 | (quality adj2 (wellbeing or well being)).ti,ab. |
| 43 | sickness impact profile.ti,ab. |
| 44 | disability adjusted life.ti,ab. |
| 45 | (qal* or qtime* or qwb* or daly*).ti,ab. |
| 46 | (euroqol* or eq5d* or eq 5*).ti,ab. |
| 47 | (qol* or hql* or hqol* or h qol* or hrqol* or hr qol*).ti,ab. |
| 48 | (health utility* or utility score* or disutilit* or utility value*).ti,ab. |
| 49 | (hui or hui1 or hui2 or hui3).ti,ab. |
| 50 | (health* year* equivalent* or hye or hyes).ti,ab. |
| 51 | discrete choice*.ti,ab. |
| 52 | rosser.ti,ab. |
| 53 | (willingness to pay or time tradeoff or time trade off or tto or standard gamble*).ti,ab. |
| 54 | (sf36* or sf 36* or short form 36* or shortform 36* or shortform36*).ti,ab. |
| 55 | (sf20 or sf 20 or short form 20 or shortform 20 or shortform20).ti,ab. |
| 56 | (sf12* or sf 12* or short form 12* or shortform 12* or shortform12*).ti,ab. |
| 57 | (sf8* or sf 8* or short form 8* or shortform 8* or shortform8*).ti,ab. |
| 58 | (sf6* or sf 6* or short form 6* or shortform 6* or shortform6*).ti,ab. |
| 59 | or/38-58 |
| 60 | 23 and 37 |
| 61 | limit 60 to yr="2014 -Current" |
| 62 | 23 and 59 |

**NHS EED and HTA (CRD) search terms**

| | |
|---|---|
| 1 | MeSH DESCRIPTOR Accidental Falls EXPLODE ALL TREES |
| 2 | ((fall or falls or falling or faller* or fallen or slip* or trip or trips or tripped or tripping or tumbl*)) |
| 3 | #1 OR #2 |
| 4 | (#3) IN NHSEED |

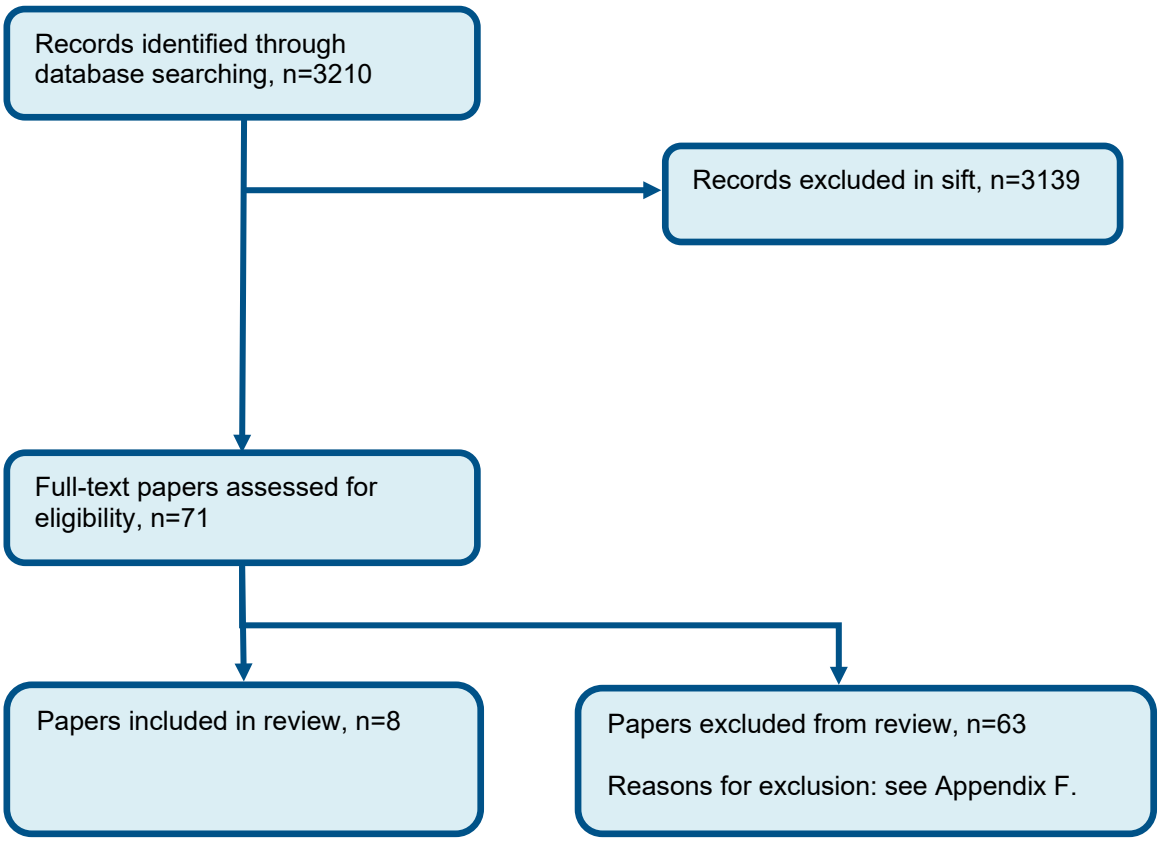
| | |
|---|---|
| 5 | (#3) IN HTA |

**INAHTA search terms**

| | |
|---|---|
| 1 | ("Accidental Falls"[mh]) OR (fall or falls or falling or faller* or fallen or slip* or trip or trips or tripped or tripping or tumbl*) |
| 2 | limit to english language |
| 3 | 2004 - current |

# Appendix C Prognostic evidence study selection

**Figure 1:** Flow chart of clinical study selection for the review of electronic patient records for identifying falls in older people



# Appendix D Prognostic evidence

| Reference | Archer, 2024[1] |
|---|---|
| Study type | Retrospective cohort study |
| Study sample | External validation was performed in Connected Bradford, which includes linked health and social care data from around 800,000 residents of Bradford and Airedale, located in the north of England. The included data span five NHS Trusts, 86 general practices and linked health, education, social care, environmental and local government data. External validation took place in patients registered with a Connected Bradford general practice on 1 January 2019. |
| Inclusion criteria | Eligible patients were defined as those with linked data, aged ≥65 years. |
| Exclusion criteria | Not specified |
| Risk tools | eFalls prediction model |
| Outcome | The outcome was any (one or more) ED attendance or hospital admission for a fall or fracture (as an indicator of an injurious fall) within 12 months of their baseline predictor assessment. Outcomes were identified in SAIL through linkage with the Emergency Department Dataset and Patient Episode Database for Wales and in Connected Bradford through linked secondary care data. A list of ICD-10 codes used to define fall/fractures was included in the study appendix.<br>12 month follow-up period. |
| Results | 81685 electronic health records from the external validation cohort<br>Fallers/fracture: 2389<br>Non-Fallers/fractures: 79296<br>c-statistic= 0.82 (0.801- 0.830)<br>Calibration slope = 1.20 (1.13- 1.27)<br>Calibration-in-the-large = -0.87 (-0.96 to -0.78)<br>Sensitivity and specificity data – reported in table 10 |
| Funding | This research was funded by the NIHR Health Technology Assessment (HTA) programme (unique award identifier NIHR127905). L.A. and R.R. are supported by funding from the NIHR Birmingham Biomedical Research Centre (BRC) at the University Hospitals Birmingham NHS Foundation Trust and the University of Birmingham. A.C. is part-funded by the National Institute for Health Research Applied Research Collaboration Yorkshire & Humber, the NIHR Leeds BRC and Health Data Research UK, an initiative funded by UK Research and Innovation Councils, NIHR and the UK devolved administrations and leading medical research charities. J.H., A.A. and R.A.L. were supported by Health and Care research Wales [Projects: SCG-19-1654, SCF-18-1504] and Health Data Research UK [HDR-9006], which receives its funding from HDR UK Ltd funded by the UK Medical Research Council, |

| Reference | Archer, 2024[1] |
|---|---|
| | Engineering and Physical Sciences Research Council, Economic and Social Research Council, Department of Health and Social Care (England), Chief Scientist Office of the Scottish Government Health and Social Care Directorates, Health and Social Care Research and Development Division (Welsh Government), Public Health Agency (Northern Ireland), British Heart Foundation (BHF) and the Wellcome Trust. A.A. and R.A.L. are also funded by the Economic and Social Research Council through Administrative Data Research UK (ES/S007393/1). |
| Limitations (risk of bias and indirectness) | This study was marked down due to outcome indirectness. The outcome was limited to patients who experienced injurious falls, which could exclude populations who experience non-injurious falls. High risk of bias was reported due to lack of information on exclusion criteria. |

| Reference | Chu, 2022[2] |
|---|---|
| Study type | Cohort study |
| Study sample | Hospitalised participants on geriatric unit in a Taiwanese hospital.1,101 elderly patients were subsequently analysed. |
| Inclusion criteria | Not specified |
| Exclusion criteria | Not specified |
| Risk tools | XGBoost, Light GBM, Random Forest, DNN, Logistic regression, and SGD. |
| Outcome | Fall risk. No specified follow-up period. |
| Results | Mean age of patients was 86.08 years. Identified comorbidities included visual impairment, hearing impairment, urinary incontinence, difficulty in communication and sleep disturbances. XGBoost reported the highest accuracy, whereas SGD reported the lowest accuracy. XGBoost also reported the highest sensitivity and DNN reported the lowest level of sensitivity. LightGBM and Random Forest both reported the highest specificity, whereas the lowest specificity was reported by DNN. |
| Funding | The study was supported by the Taichung Veterans General Hospital, Taiwan (Grant number: TCVGH-T1097801 awarded to W-MC). |
| Limitations (risk of bias and indirectness) | No concern regarding study directness. Very high risk of bias was reported. |

| Reference | Dormosh 2022a[6] |
|---|---|
| Study type | Retrospective, population-based cohort study |
| Study sample | 36470 community-dwelling participants in the Netherlands. |
| Inclusion criteria | Patients registered with any general practitioner in the network at any time in the period from 2018 to 2019. Patients were included in the study cohort if they were 65 years or older at the beginning of the observation period. |
| Exclusion criteria | Individuals whose predictors of the chronic condition groups were obtained from previous years and individuals and who did not consult a GP in the follow up period. |
| Risk tools | Electronic patient records with an automated search strategy as an algorithm for the identification of the value of "history of falls" from the free text and applied to the observation period before the index date. "History of falls" in the observation period is a (derived) candidate predictor like the other predictors. The algorithm consists of a regular expression search of trigger words, detection of negation, and coexistence of words that either refer to traffic accidents (outside the study definition of "fall") or indicate that "fall" was not used in the sense of "falling" (eg "fall season"). |
| Outcome | Any fall during the 1-year follow-up period. Data on falls were obtained from the free text written during the follow-up period. |
| Results | 36470 electronic health records.<br>Fallers: 4778<br>Non-Fallers: 31692<br>Sensitivity= 0.623 (0.593- 0.664)<br>Specificity = 0.698 (0.665- 0.740)<br>Median age of participants was 76.6 years.<br>History of falls was identified as being the strongest predictor for future falls, followed by depression and memory and concentration problems. |
| Funding | The work was supported by the Netherlands Organization for Health Research and Development (ZonMw; grant number 628011026), The Hague, the Netherlands. |
| Limitations (risk of bias and indirectness) | Laboratory measurements were excluded from the analysis. Indirectness was not a concern in this study. The study was identified as being at a serious risk of bias due to limited reporting of outcome definitions. |

| Reference | Dormosh 2022b[4] |
|---|---|
| Study type | Retrospective, population-based cohort study |
| Study sample | Enlisted community dwelling patients aged 65 years or older in the Netherlands. |
| Inclusion criteria | Patients aged 65 years or older enlisted with a GP between 2018 and 2019. |
| Exclusion criteria | Participants were excluded if they died during the observation period or were registered during the follow-up period. |

| Reference | Dormosh 2022b[4] |
|---|---|
| Risk tools | Risk prediction model using text searching of electronic patient records. |
| Outcome | Any fall during the 1-year follow-up period. |
| Results | Fallers: 5124<br>Non-Fallers: 33009<br>ROCAUC: 0.690 (0.686- 0.698) |
| Funding | This work was supported by the Netherlands Organization for Scientific Research (NWO) (grant number 628011026), the Hague, the Netherlands. |
| Limitations (risk of bias and indirectness) | Directness was not a concern for this study. This study has a high risk of bias due to the limited provision of provision of predictor information. |

| Reference | Dormosh 2023a |
|---|---|
| Study type | Retrospective cohort study |
| Study sample | Primary care EHR data of people aged 65 or over. Study sample included patients enlisted with GPs between 2018 and 2019. Baseline data (structured clinical variable and unstructured clinical notes) were obtained from the observation period in the year 2018. Data in the follow-up period in the year 2019 were used to determine the outcome (1-year fall). |
| Inclusion criteria | Individuals aged 65 or older at the beginning of 2018 and who had more than one word in the clinical notes written in 2018 were included. |
| Exclusion criteria | NR |
| Risk tools | Risk prediction model using text searching of electronic patient records unstructed clinical notes. |
| Outcome | The outcome was defined as any fall event that occurred in the 1-year follow-up period and was ascertained by a manual chart review of the clinical notes associated with patients in the follow-up period. |
| Results | Fallers: = 4,778<br>Non-Fallers: = 31,692<br><br>Natural language processing of unstructured clinical data from electronic health records - Topic-based model AUC: 0.685 (0.676–0.694)<br>Natural language processing of unstructured clinical data from electronic health records - Combi model AUC: 0.718 (0.708–0.727) |

| Reference | Dormosh 2023a |
|---|---|
| | Natural language processing of unstructured clinical data from electronic health records - Baseline model: AUC: 0.709 (0.700–0.719) |
| Funding | This work was supported by the innovation funds of Amsterdam UMCeLocation AMC. The sponsor did not have any role or influence in study design analysis or reporting. |
| Limitations (risk of bias and indirectness) | Directness was not a concern for this study. This study has a high risk of bias |

| Reference | Dormosh 2023b |
|---|---|
| Study type | Retrospective cohort study |
| Study sample | All hospital admissions with a minimal length of stay of 24 hours (between January 2016 and January 2021). |
| Inclusion criteria | patients aged 70 years or older who did not experience falls during the first 24 hours of admission. |
| Exclusion criteria | NR |
| Risk tools | 2 risk prediction models using text searching of electronic patient records. |
| Outcome | The outcome was the occurrence of any inpatient fall after 24 hours of hospital admission and during the hospital stay, regardless whether the patient fell multiple times or not. |
| Results | Fallers: 470<br>Non-Fallers: 20816<br><br>Fall prediction model (Without indicators for Missing Values) AUC: 0.676 (0.645- 0.707)<br>Fall prediction model (With indicators for Missing Values) AUC: 0.695 (0.667- 0.724) |
| Funding | This work was supported by the innovation funds of Amsterdam UMCeLocation AMC. The sponsor did not have any role or influence in study design analysis or reporting. |
| Limitations (risk of bias and indirectness) | Directness was not a concern for this study. This study has a high risk of bias |

| Reference | Marier 2016[7] |
|---|---|
| Study type | Cohort study |
| Study sample | Nursing home residents comprising of 5129 residents across 13 nursing homes within a single large chain in California. |
| Inclusion criteria | Not specified |
| Exclusion criteria | Not specified |
| Risk tools | The minimum data set (MDS) is a standardised Centers for Medicare and Medicaid Services screening and assessment tool for residents in a Medicare and/or Medicaid-certified nursing home in the United States. MDS contains information regarding risk factors related to falls. The included models using MDS assessments alone, MDS assessments and EMR data alone, MDS assessments and EMR duplicates, or MDS assessments, EMR data alone and EMR duplicates combined. |
| Outcome | Fall risk |
| Results | The proportion of observed falls declined as participants at a lower risk were identified. Participants accounting for the lowest projected risk decile accounted for 2% of observed falls. Models 1 and 2 appear to perform similarly in participants at lower projected risk deciles. In higher risk deciles, Models 1 and 2 appear to underperform when compared to Models 3 and 4. Model 4 offers no improvement when compared to Model 3. Replacing MDS risk factor measures with frequently updated EMR data appears to improve identification for nursing home residents at the highest risk for falls. |
| Funding | The work was funded by the Agency for Healthcare Research & Quality (AHRQ), Department of Health & Human Services (DHHS), under contract # HHSA290201000031I. |
| Limitations (risk of bias and indirectness) | Directness was a concern for this study.<br>The authors noted that the EMR system used for the nursing home chain was customised for the chain, impacting the applicability of the study. The study was identified as being of high risk of bias due to insufficient reporting of inclusion and exclusion criteria. |

| Reference | Pajewski 2019[9] |
|---|---|
| Study type | Cohort study |
| Study sample | Patients with information in the Medicare Accountable Care Organization. |
| Inclusion criteria | Patients who were at least 65 years old by 1 July 2016. |
| Exclusion criteria | Patients were excluded if they did not have information regarding at least 9 out of 20 items based on laboratory measurements, smoking status, body mass index, and blood pressure measured in the past 2 years. |
| Risk tools | electronic frailty index (eFI) |

| Reference | Pajewski 2019[9] |
|---|---|
| Outcome | Injurious falls according to ICD-10 codes and linked with an emergency department visit |
| Results | Patients with sufficient data to calculate eFI: 9013<br>Patients with insufficient data to calculate eFI: 3785<br>C-statistic: 0.791<br>When accounting for age, comorbidity, and prior health care utilisation, eFI was able to independently predict injurious falls. The authors note that comorbidity was not a significant predictor of injurious falls. |
| Funding | The project was supported by the National Center for Advancing Translational Sciences (NCATS) and the National Institutes of Health (UL1TR001420). Additional funding support was provided by the Wake Forest University Claude D. Pepper Older Americans Independence Center (P30-AG21332), the J. Paul Sticht Center for Health for Healthy Aging and Alzheimer's Disease, and the Center for Health Care Innovation at Wake Forest School of Medicine. |
| Limitations (risk of bias and indirectness) | The outcome was limited to patients who experienced injurious falls, which could exclude populations who experience non-injurious falls. Indirectness is a concern in this study. This study was identified as having a high risk of bias due to insufficient explanation regarding the evaluation of the models. |

| Reference | Patterson 2019[10] |
|---|---|
| Study type | Retrospective observational study |
| Study sample | Electronic health record data for patients aged 65 years or older who visited the emergency department at a single academic hospital. |
| Inclusion criteria | Patients aged 65 years or older who visited the emergency department with additional six month follow-up data |
| Exclusion criteria | Patients whose visits resulted in hospital admissions, patients who were transferred from other healthcare facilities, and patients who did not have a primary care provider within the specified network. |
| Risk tools | Random Forest, AdaBoost, and regression-based models including Logistic regression, Linear regression, LASSO Logistic regression, and RIDGE Logistic regression. |
| Outcome | Fall risk |
| Results | When compared to patients who did not return to the emergency department for falls, those who had experienced a fall were similar in regards of gender and insurance status. However, those who did fall were more likely to be older and have experienced a fall on their index visit. The Random Forest model and the AdaBoost model each achieved an AUC of 0.78. |
| Funding | The work was supported by funding from the Agency for Healthcare Research and Quality (AHRQ), Grant numbers: K08HS024558 (BWP), and K08HS024342 (MSP), as well as the NIH, grant numbers K08DK111234 (MDR) and K24AG054560 (MNS). Research |

| Reference | Patterson 2019[10] |
|---|---|
| | was also supported by the Clinical and Translational Science Award (CTSA) program, through the NIH National Center for Advancing Translational Sciences (NCATS), Grant UL1TR000427. |
| Limitations (risk of bias and indirectness) | Directness was not a concern in this study. This study was identified as being of high risk of bias due to predictor knowledge being based on fall risk predictive value. |

| Reference | Thapa 2022[11] |
|---|---|
| Study type | Retrospective study |
| Study sample | Older patients in skilled nursing facilities, independent living facilities, and assisted living facilities in the United States. |
| Inclusion criteria | Residents with first and last measurement times, residents with diagnosis codes, residents over 60 years old, and residents with at least 1+3 month data before last measurement time. |
| Exclusion criteria | Residents aged 60 years or younger. |
| Risk tools | Machine learning algorithms including XGBoost, logistic regression, and multilayered perceptron. |
| Outcome | Short-term falls risk (falls at 3 months) |
| Results | 2785 residents were included in the study, with 153 residents identified as experiencing a fall within 3 months. Mean age among fallers and non-fallers was 86.6 years and 85.7 years, respectively. XGBoost was noted to have the highest level of performance with an AUC of 0.846 (95%CI 0.794- 0.894). XGBoost also noted high specificity (0.848) and sensitivity (0.706).<br>The authors note the number of active medications was the most significant factor associated with fall risk. |
| Funding | Not specified |
| Limitations (risk of bias and indirectness) | Directness was not a concern in this study. This study was identified as being of high risk of bias due to prior knowledge of predictors when determining the outcome. |

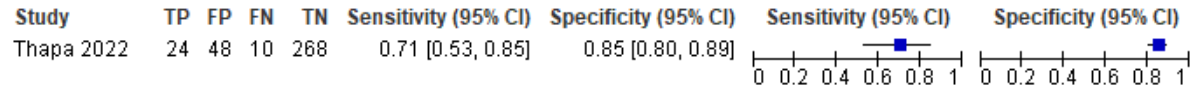
| Reference | Ye 2020[12] |
|---|---|
| Study type | Cohort study |
| Study sample | 265,225 individuals were recruited in this study. |
| Inclusion criteria | Patients aged 65 years or older and had health care facilities access. |
| Exclusion criteria | Aged 65 years or younger or individuals who did not have any active encounter for one year or died before 1 April 2016. |

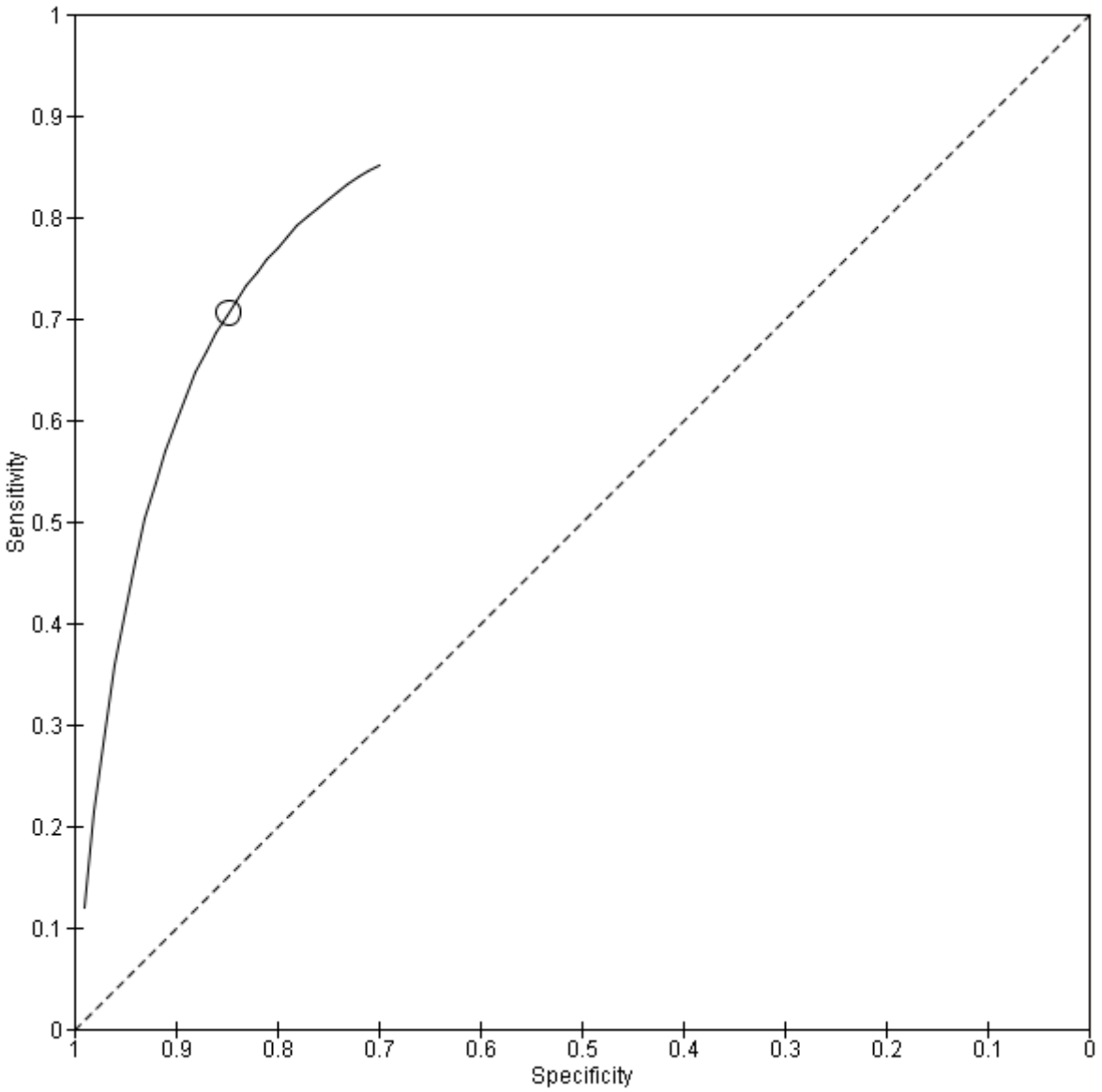
| Reference | Ye 2020[12] |
|---|---|
| Risk tools | Prediction model developed from XGBoost, Support Vector Machine (SVM), K-nearest neighbors (KNN), Lasso, and Random Forest. |
| Outcome | Fall risk in the following year |
| Results | The validation cohort, which was comprised of 88409 participants, had a C-statistic of 0.807. The authors note that the model identified 43.4% of falls in advance through the following year. |
| Funding | One author was supported by the National Natural Science Foundation of China (Award No.81402762). |
| Limitations (risk of bias and indirectness) | Directness was not a concern for this study.<br>The study was identified as being of unclear risk of bias due to insufficient reporting. |

# Appendix E Forest plots

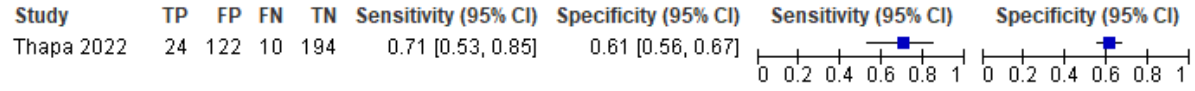
Forest plots from data available from Thapa 2022[11].

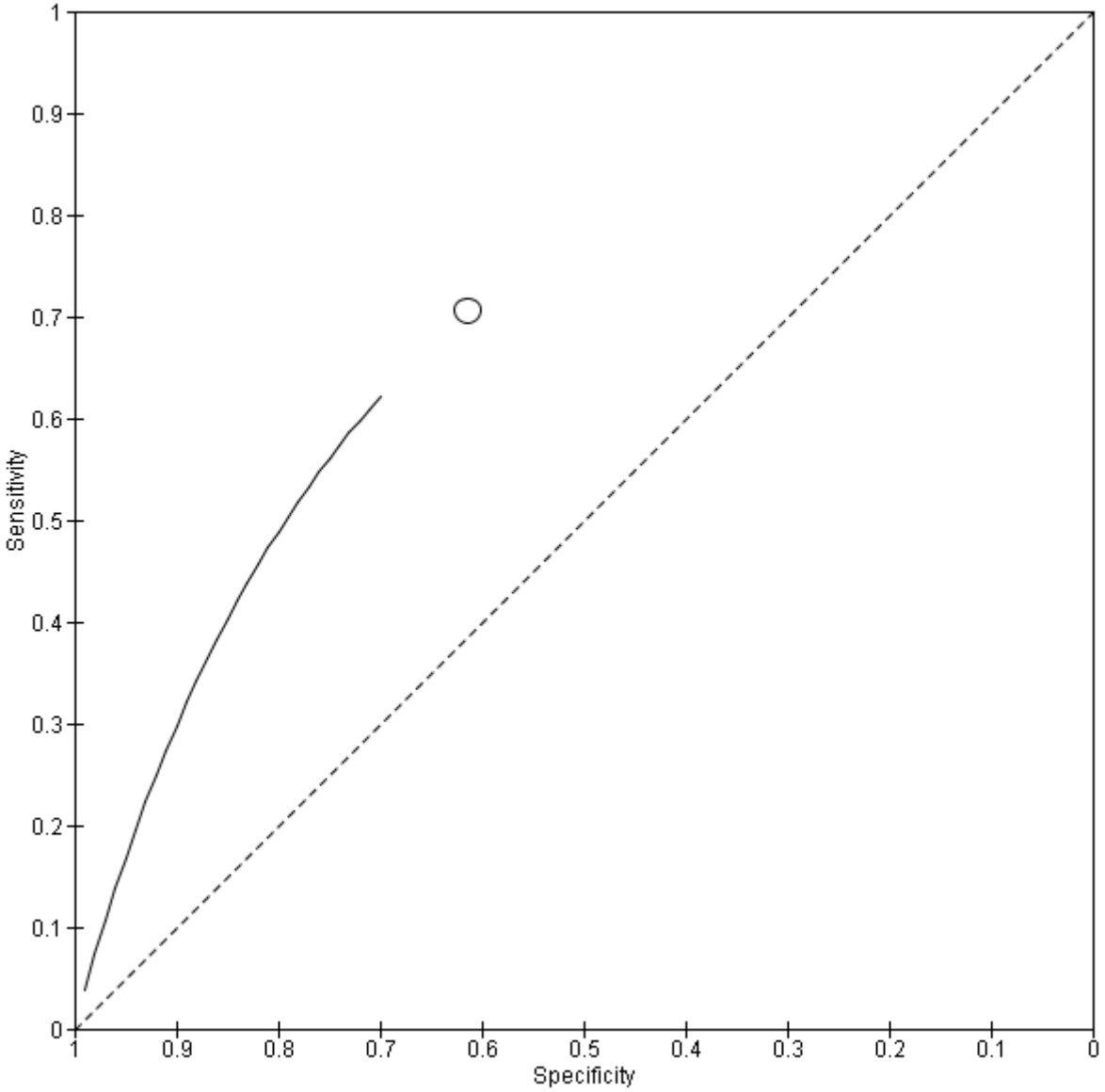
XGBoost



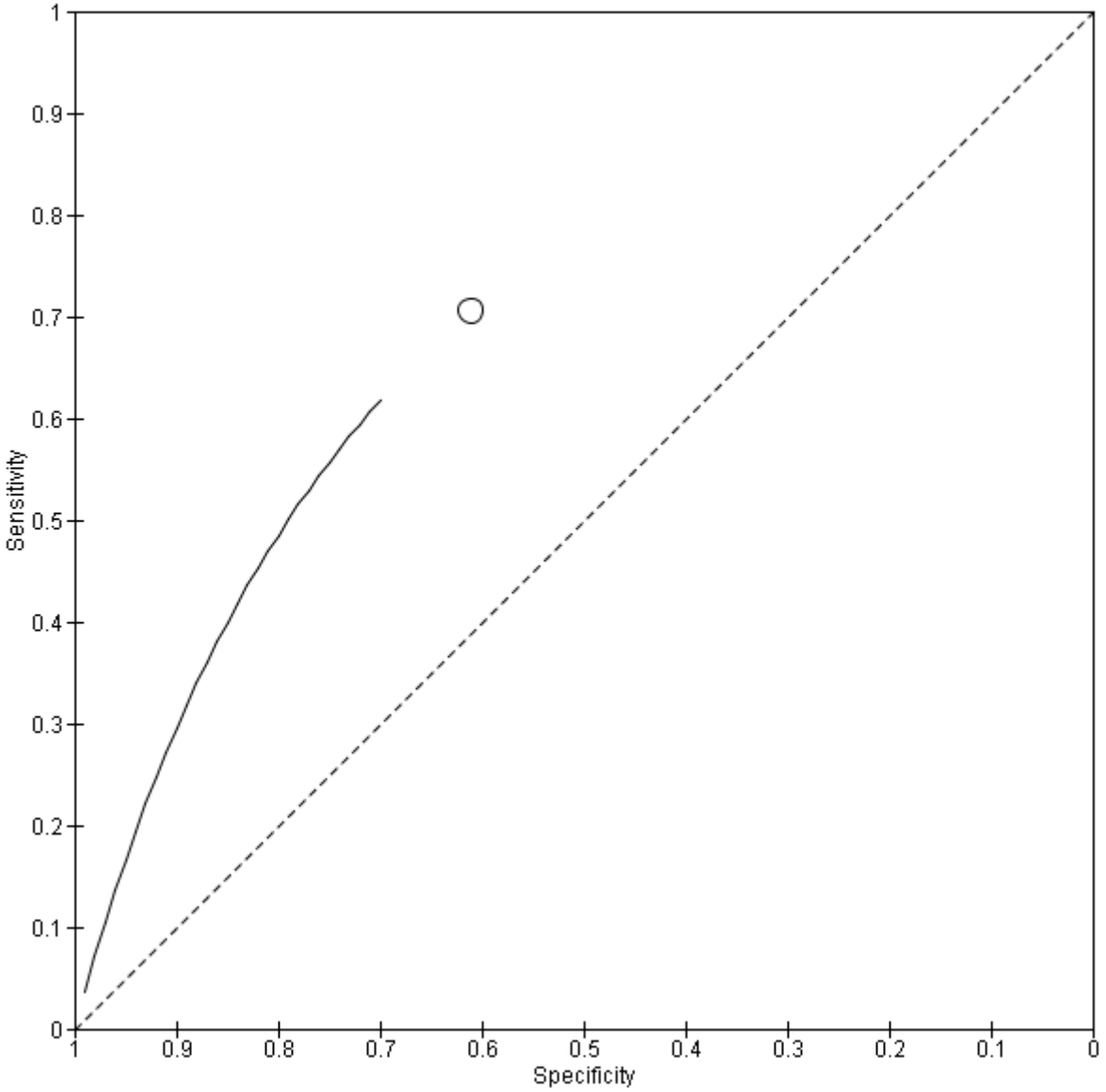

Logistic Regression





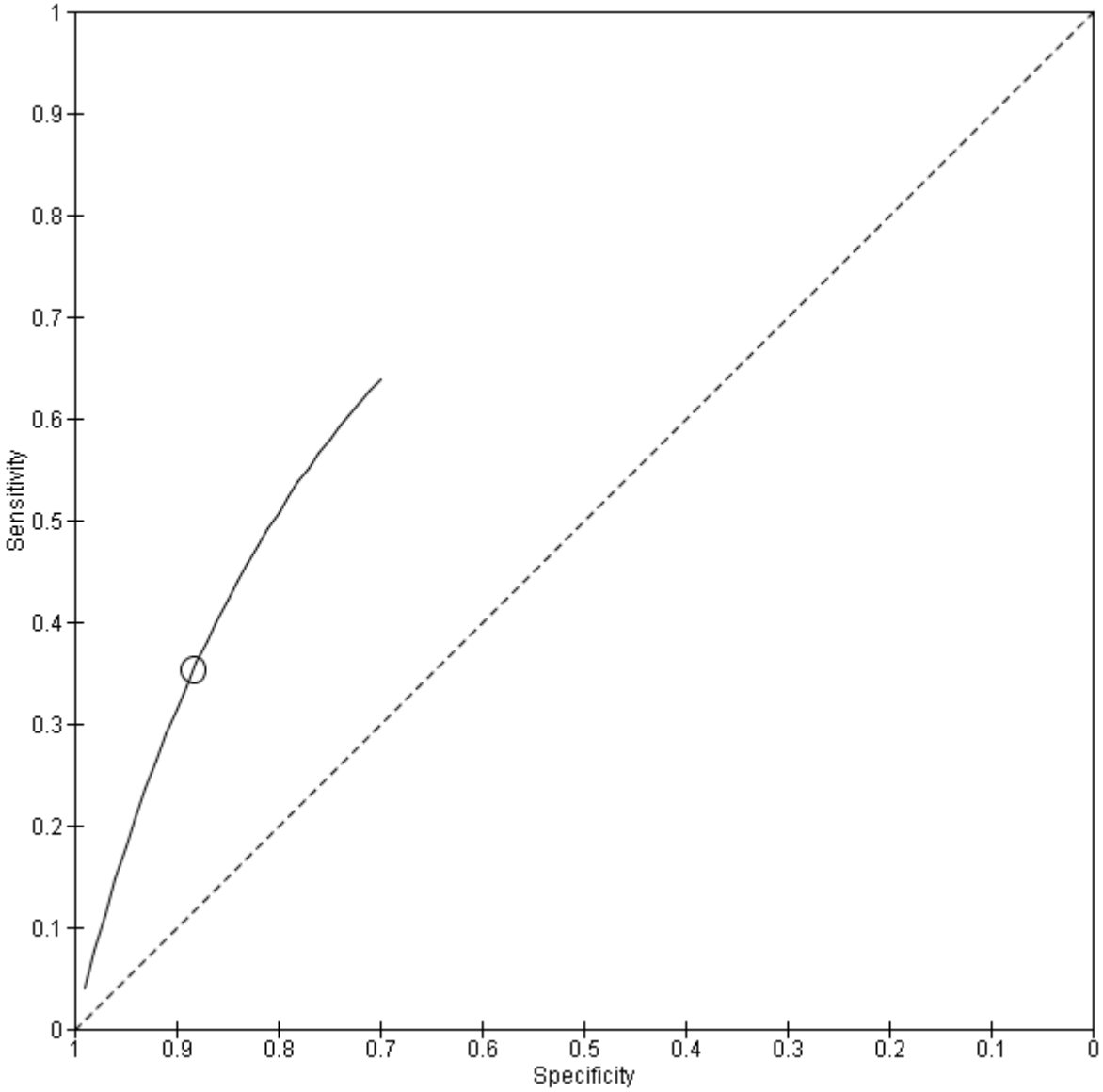

Multilayered Perceptron

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Thapa 2022 | 24 | 123 | 10 | 193 | 0.71 [0.53, 0.85] | 0.61 [0.55, 0.66] | | |

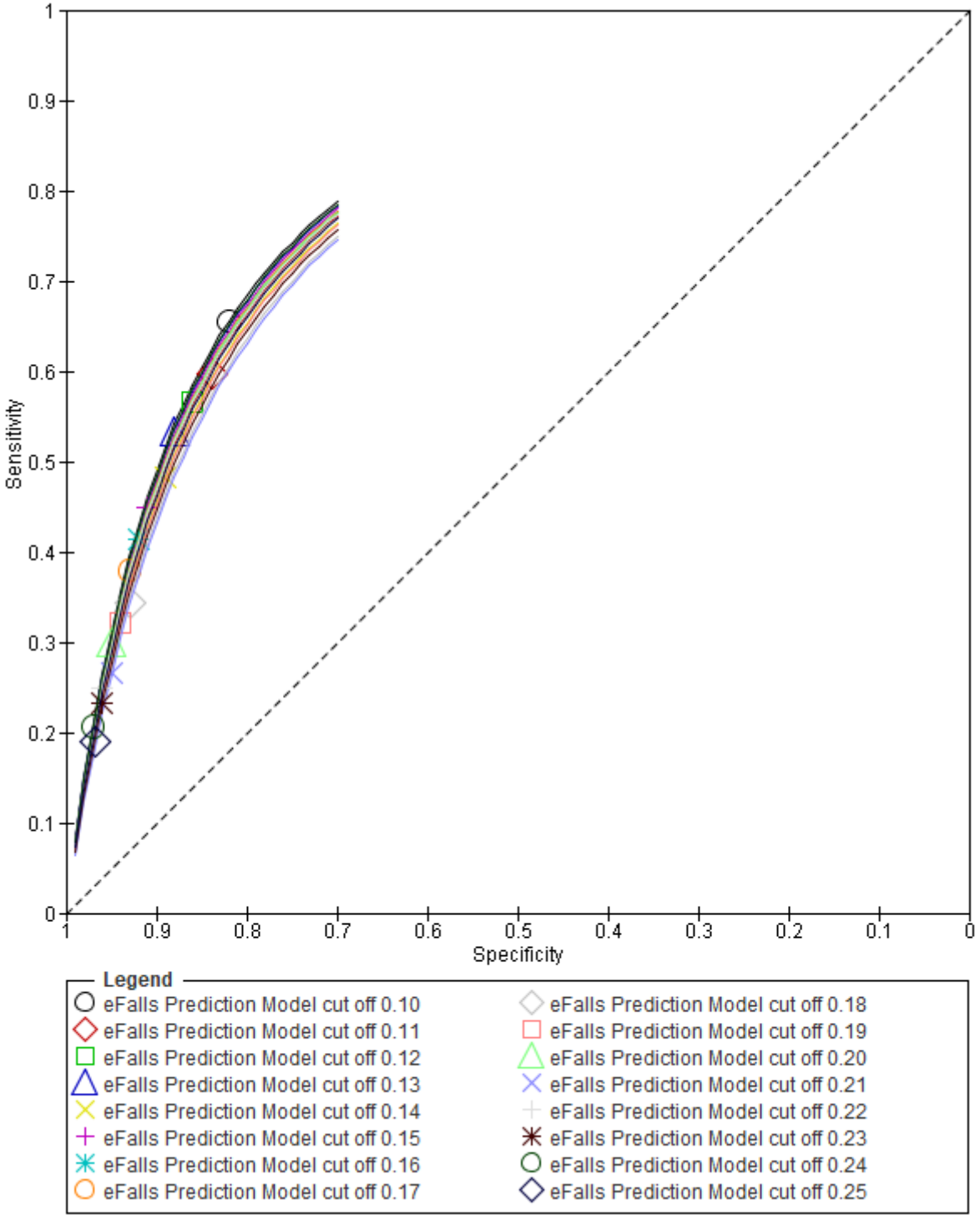



Juniper falls risk assessment score

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Thapa 2022 | 12 | 37 | 22 | 279 | 0.35 [0.20, 0.54] | 0.88 [0.84, 0.92] | | |


Sensitivity
Specificity
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

eFalls Prediction Model



**eFalls Prediction Model cut off 0.10**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 19 | 175 | 10 | 796 | 0.66 [0.46, 0.82] | 0.82 [0.79, 0.84] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.11**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 18 | 155 | 12 | 815 | 0.60 [0.41, 0.77] | 0.84 [0.82, 0.86] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.12**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 17 | 136 | 13 | 834 | 0.57 [0.37, 0.75] | 0.86 [0.84, 0.88] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.13**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 16 | 116 | 14 | 853 | 0.53 [0.34, 0.72] | 0.88 [0.86, 0.90] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.14**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 14 | 107 | 15 | 865 | 0.48 [0.29, 0.67] | 0.89 [0.87, 0.91] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.15**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 13 | 87 | 16 | 884 | 0.45 [0.26, 0.64] | 0.91 [0.89, 0.93] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.16**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 12 | 78 | 17 | 894 | 0.41 [0.24, 0.61] | 0.92 [0.90, 0.94] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.17**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 11 | 68 | 18 | 903 | 0.38 [0.21, 0.58] | 0.93 [0.91, 0.95] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.18**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 10 | 68 | 19 | 903 | 0.34 [0.18, 0.54] | 0.93 [0.91, 0.95] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.19**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 9 | 58 | 19 | 914 | 0.32 [0.16, 0.52] | 0.94 [0.92, 0.95] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.20**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 9 | 49 | 21 | 922 | 0.30 [0.15, 0.49] | 0.95 [0.93, 0.96] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.21**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 8 | 49 | 22 | 922 | 0.27 [0.12, 0.46] | 0.95 [0.93, 0.96] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.22**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 7 | 39 | 21 | 933 | 0.25 [0.11, 0.45] | 0.96 [0.95, 0.97] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.23**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 7 | 39 | 23 | 931 | 0.23 [0.10, 0.42] | 0.96 [0.95, 0.97] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.24**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 6 | 29 | 23 | 942 | 0.21 [0.08, 0.40] | 0.97 [0.96, 0.98] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

**eFalls Prediction Model cut off 0.25**

| Study | TP | FP | FN | TN | Sensitivity (95% CI) | Specificity (95% CI) | Sensitivity (95% CI) | Specificity (95% CI) |
|---|---|---|---|---|---|---|---|---|
| Archer 2024 | 5 | 29 | 21 | 944 | 0.19 [0.07, 0.39] | 0.97 [0.96, 0.98] | 0 0.2 0.4 0.6 0.8 1 | 0 0.2 0.4 0.6 0.8 1 |

# Appendix F Listed Predictors

## F.1 Thapa 2022[11] List of Predictors

Vitals (respiratory rate, diastolic blood pressure, systolic blood pressure, heart rate, temperature), labs (glucose, CO2, sodium, creatinine, potassium, calcium, chloride, blood urea nitrogen, albumin, cholesterol), demographics (age, sex), physical (height, weight, lower extremity fracture or dislocation, history of fall), comorbidities (chronic kidney disease, cancer, diabetes, hypertension, chronic heart failure, dementia, chronic obstructive pulmonary disease, myocardial infarction, arrhythmia, other mental behaviours or disorders, schizophrenia or psychosis, mood or affective disorders or somatoform, movement disorder, lower extremity fracture, vertebrae and neck fracture, healed fractures, stroke and cerebrovascular, history of all, abnormal gait, weakness, dizziness, and unsteadiness, vertigo), medications (antiepileptic, anticonvulsant, benzodiazepine, antidepressants, narcotics, diuretics, beta blockers, anticholinergics antimuscarinics, antispasmodics, antipsychotics, neuromuscular blocking agents, antihistamines, calcium channels, antiarrhythmics, angiotensin converting enzyme inhibitors, alpha adrenergic blocking agents, sedative hypnotic, number of active medications).

## F.2 Marier 2016[7] List of Predictors

A prior fall in the last 6 months, full ambulation, wheelchair use, use of walking aids, an unsteady gait or imbalance, wandering, osteoporosis, anaemia, epilepsy, use of antianxiety, antipsychotic, or antidepressant medications, and dementia.

## F.3 Dormosh 2022a[6] List of Predictors

A total of 79 predictors known to be associated with falls were included. Demographic predictors included age in years (at the beginning of the observational period) and sex. Medication predictors used were coded using the Anatomical Therapeutic Chemical (ATC) classification system. The International Classification of Primary Care (ICPC) is the standard for coding and classification of complaints, symptoms, and disorders in general practice in the Netherlands. ICPC codes were grouped into 43 chronic condition groups according to previous classification and expert knowledge. Predictors identified in the final prediction model for future falls included age, female sex, history of falls, use of proton pump inhibitors, use of opioids, previous injury, depression, osteoarthritis, urinary incontinence, and memory and concentration problems.

## F.4 Dormosh 2022b[4] List of Predictors

10 predictors including age, sex, proton pump inhibitors, opioids, previous injury, depression, osteoarthritis, urinary incontinence, memory and concentration problems, and history of falls.

## F.5 Pajewski 2019[9] List of Predictors

Diagnosis codes including: anaemia, rheumatoid arthritis or osteoarthritis, atrial fibrillation, stroke or transient ischemic attack, renal disease, diabetes, dizziness or vertigo, dyspnoea, falls, fragility or fracture, hearing impairment, congestive heart failure, valvular disease, hypertension (uncomplicated and complicated), hypotension/ syncope, myocardial infarction, coronary atherosclerosis and other heart disease, melanoma, blood-related cancer, cancer (excluding melanoma, blood-related or skin cancer), dementia, osteoporosis, Parkinson's disease, peptic ulcer, peripheral vascular disease, pulmonary disease, skin ulcer, thyroid disease, urinary incontinence, urinary system disease, blindness and other vision defects, weight loss, depression, mild liver disease, moderate or severe liver disease, and chronic

pain. Laboratory measures and vital signs including: obesity (body mass index), underweight (body mass index), systolic blood pressure (BP), diastolic blood pressure (BP), eGFR (CKD-EPI equation), HDL cholesterol, total cholesterol, triglycerides, potassium, sodium, aspartate aminotransferase (SGOT), mean corpuscular volume, blood urea nitrogen, calcium, albumin, total protein, alkaline phosphatase, haemoglobin, and glucose. Functional data including: smoking, polypharmacy, activities of daily living, instrumental activities of daily living, self-reported health status, can perform rise from a chair without using arms, diagnosis of dementia or cognitive impairment, hearing concerns or use of hearing aid, overall stress level (does stress affect daily life), and typical amount of pain (does pain affect daily life).

## F.6 Ye 2020[12] List of predictors

157 impactful predictors (top 55 specified in supplemental material) were captured out of a pool of 10,198 predictor candidates. Age, female gender, abnormalities of gait and balance, anaemia, cognitive disease, gout, urinary disease, cardiovascular disease, muscle disorders, orthostatic hypotension, hypertension, lipid disorders, heart failure, cerebral infarction, Parkinson's disease, epilepsy and recurrent seizures, osteoporosis, abrasion of knee, type 2 diabetes, type 1 diabetes, fall history, cardiovascular medications (including beta2-adrenergic agnoist, loop diuretic, angiotensin converting enzyme inhibitor, beta-adrenergic blocker, aldosterone antagonist, and thiazide diuretic), mental medications (including atypical antipsychotic, selective serotonin reuptake inhibitor, benzodiazepine, opioid agonist, dopamine-2 receptor antagonist, SNRI, poisoning by narcotics and psychodysleptics, and tricyclic antidepressant), NSAID, antiepileptics, cholinergic muscarinic antagonist, number of emergency visits last year, outpatient visits in the last 12 months, patient's medical costs last year, inpatient length of days last year, number of medications last year, number of distinct medications last year, number of lab tests year, number of distinct lab tests last year, number of diagnoses last year, number of distinct diagnoses last year, haemoglobin, urea nitrogen, MCHC auto, glomerular filtration rate, and natriuretic peptide B.

## F.7 Patterson 2019[10] List of predictors

age, vital signs during the index ED visit, duration of the index visit, and number of primary care or hospital visits in the six months prior to the index visit

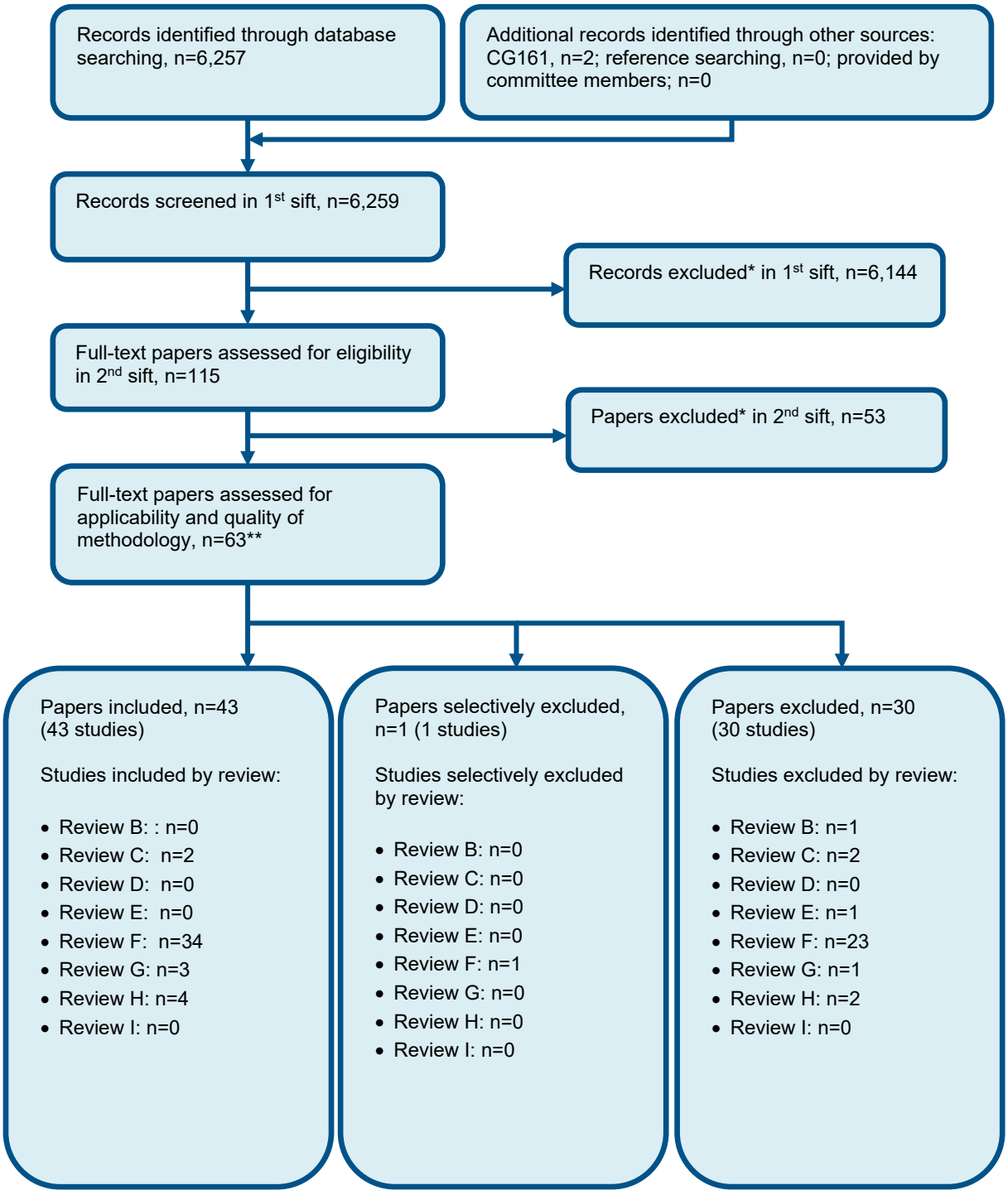
## F.8 Archer 2024[1] List of predictors

Age (years), Polypharmacy, Gender, BMI category ,Smoking, Alcohol consumption, Abdominal pain, Activity limitation , Anaemia and haematinic deficiency Asthma, Atrial fibrillation, Back pain, Bone disease, Cancer, Cognitive impairment, COPD , Dementia Depression, Diabetes mellitus, Dizziness, Dressing and grooming problems, Faecal incontinence, Falls, Fatigue, Foot problems Fracture, Fragility fracture, General mental health, Headache, Hearing impairment, Heart failure, Housebound, Hypertension, Hypotension or syncope, Inflammatory arthritis, Inflammatory bowel disease, Liver problems, Meal preparation problems Medication management, Memory concerns, Mobility problems, Mono or hemiparesis, Motor neurone disease, Musculoskeletal problems, Osteoarthritis, Osteoporosis, Palliative care, Parkinsonism and tremor, Peptic ulcer disease, Peripheral neuropathy, Peripheral vascular disease, Requirement for care, Respiratory disease, Seizures, Self-harm, Severe mental illness, Skin ulcer, Sleep problems, Social vulnerability, Stress, Stroke, Thyroid problems, Urinary incontinence, Urinary system disease, Visual impairment, Washing and bathing, Weakness, Weight loss

## F.9 Dormosh 2023b[3] List of predictors

Demographic predictors, Fall history, Health care utilization, Physiologic predictors, Biochemical predictors, Comorbidity predictors, Medication predictors, Patient risk assessment scores.

# Appendix G Economic evidence study selection




* Non-relevant population, intervention, comparison, design or setting; non-English language
**One paper included in two reviews

# Appendix H Economic evidence tables

There were no included health economic studies.

# Appendix I Health economic model

No original health economic modelling was undertaken.

# Appendix J Excluded studies

## J.1 Clinical studies

**Table 25: Studies excluded from the clinical review**

| Study | Code [Reason] |
|---|---|
| Altuhaifa, F., Al Tuhaifa, D., Al Ribh, E. et al. (2023) Identifying and defining entities associated with fall risk factors events found in fall risk assessment tools. Computer Methods and Programs in Biomedicine Update 3: 100105 | - Study does not contain an intervention relevant to this review protocol |
| Anzaldi, L.J., Davison, A., Boyd, C.M. et al. (2017) Comparing clinician descriptions of frailty and geriatric syndromes using electronic health records: a retrospective cohort study. BMC geriatrics 17(1): 248 | - Data not reported in an extractable format or a format that can be analysed |
| Arena, S.K., Rataj, J., Thompson, M. et al. (2015) Medications and fall risk indicators among patients case-managed by physical therapists. Home healthcare now 33(2): 96-102 | - Population not relevant to this review protocol |
| Azevedo, Daniela Castelo, Hoff, Leonardo Santos, Kowalski, Sergio Candido et al. (2024) Risk factors for osteoporotic hip fracture among community-dwelling older adults: a real-world evidence study. Advances in rheumatology (London, England) 64(1): 8 | - Study does not contain an intervention relevant to this review protocol |
| Baek, S., Piao, J., Jin, Y. et al. (2014) Validity of the Morse Fall Scale implemented in an electronic medical record system. Journal of clinical nursing 23(1718): 2434-2440 | - Study design not relevant to this review protocol |
| Baus, A., Coben, J., Zullig, K. et al. (2017) An Electronic Health Record Data-driven Model for Identifying Older Adults at Risk of Unintentional Falls. Perspectives in health information management 14(fall): 1b | - Population not relevant to this review protocol |
| Baus, A., Zullig, K., Long, D., Mullet, C., Pollard, C., Taylor H., Coben, J. (2016) Developing methods of repurposing electronic health record data for identification of older adults at risk of unintentional falls. Perspectives in health information management 13(1b) | - Data not reported in an extractable format or a format that can be analysed |
| Bjarnadottir, Ragnhildur I and Lucero, Robert J (2018) What Can We Learn about Fall Risk Factors from EHR Nursing Notes? A Text Mining Study. EGEMS (Washington, DC) 6(1): 21 | - Population not relevant to this review protocol |
| Block, Valerie J, Koshal, Kanishka, Wijangco, Jaeleene et al. (2024) A Closed-Loop Falls Monitoring and Prevention App for Multiple Sclerosis Clinical Practice: Human-Centered Design of the Multiple Sclerosis Falls InsightTrack. JMIR human factors 11: e49331 | - Study does not contain an intervention relevant to this review protocol |
| Bohnsack, Alanna, Faig, Karla, Cook, Allyson et al. (2023) Retrospective Use of the Pictorial Fit-Frail Scale for Determination of Frailty Level in Hospitalized Older Adults with a Hip Fracture. Canadian geriatrics journal : CGJ 26(3): 400-404 | - Study does not contain an intervention relevant to this review protocol |
| Burm, Seung Won, Hong, Namki, Lee, Seung Hyun et al. (2021) Fall Patterns Predict Mortality After Hip Fracture in Older Adults, | - Study design not relevant to this review protocol |

| Study | Code [Reason] |
|---|---|
| Independent of Age, Sex, and Comorbidities. Calcified tissue international 109(4): 372-382 | |
| Camargo Alves, Renata; Barreto Colichi, Rosana Maria; Molina Lima, Silvana Andrea (2023) Analysis of patent records related to the prevention and signaling of falls in Brazil. Revista Gaucha de Enfermagem 44: 1-16 | - Study does not contain an intervention relevant to this review protocol |
| Cano-Escalera, G., Grana, M., Irazusta, J. et al. (2023) Mortality Risks after Two Years in Frail and Pre-Frail Older Adults Admitted to Hospital. Journal of Clinical Medicine 12(9): 3103 | - Study does not contain an intervention relevant to this review protocol |
| Cardoso, Éder Kröeff, Pereira, Francisca dos Santos, Bidart, Tainá da Silva et al. (2024) INFLUENCE OF SOCIAL ISOLATION CAUSED BY COVID-19 IN ELDERLY PEOPLE HOSPITALIZATION ASSOCIATED WITH FALLS IN AN EMERGENCY HOSPITAL...1st Student Scientific Conference of the Brazilian Association for Research and Postgraduate in Physiotherapy (ABRAPG-FT), May 19-21, 2023 (Online). Brazilian Journal of Physical Therapy 28: npag-npag | - Study does not contain an intervention relevant to this review protocol |
| Carroll, Chad, Arnold, Lea Ann, Eberlein, Bill et al. (2022) Comparison of Two Different Models to Predict Fall Risk in Hospitalized Patients. Joint Commission journal on quality and patient safety 48(1): 33-39 | - Population not relevant to this review protocol |
| Casey, Colleen M, Parker, Erin M, Winkler, Gray et al. (2017) Lessons Learned From Implementing CDC's STEADI Falls Prevention Algorithm in Primary Care. The Gerontologist 57(4): 787-796 | - Study design not relevant to this review protocol |
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| Choi, E., Lee, Y., Yang, E. et al. (2016) Exploration of Risk Factors for Falls Using Electronic Nursing Records. Studies in health technology and informatics 225: 637-638 | - Study does not contain an intervention relevant to this review protocol |

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| Choi, Y., Staley, B., Henriksen, C. et al. (2018) A dynamic risk model for inpatient falls. American Journal of Health-System Pharmacy 75(17): 1293-1303 | - Population not relevant to this review protocol |
| Chua, M.T., Pan, D.S.T., Lee, M.Z. et al. (2023) Comparing Comorbidity Polypharmacy Score and Charlson Comorbidity Index in predicting outcomes in older trauma patients. Injury 54(4): 1113-1118 | - Study does not contain an intervention relevant to this review protocol |
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| Gaspar, A.G.M. and Lapao, L.V. (2022) A Digital Health Service for Elderly People with Balance Disorders and Risk of Falling: A Design Science Approach. International Journal of Environmental Research and Public Health 19(3): 1855 | - Study does not contain an intervention relevant to this review protocol |
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| Hammontree, Stephanie, Potts, Maryellen, Neiberger, Adam et al. (2023) Outpatient Oncology Fall Risk: A Quality Improvement Project. Kansas journal of medicine 16: 200-206 | - Study does not contain an intervention relevant to this review protocol |
| Hars, M., Audet, M.-C., Herrmann, F. et al. (2018) Functional Performances on Admission Predict In-Hospital Falls, Injurious Falls, and Fractures in Older Patients: A Prospective Study. Journal of Bone and Mineral Research 33(5): 852-859 | - Study does not contain an intervention relevant to this review protocol |
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| Heikkila, Anniina; Lehtonen, Lasse; Junttila, Kristiina (2024) Consequences of Inpatient Falls in Acute Care-A Retrospective Register Study. Journal of patient safety | - Study does not contain an intervention relevant to this review protocol |
| Hsu, Y. and Kao, Y.-S. (2023) Can the Electronic Health Record Predict Risk of Falls in Hospitalized Patients by Using Artificial Intelligence? A Meta-analysis. Computers, informatics, nursing : CIN 41(7): 531-538 | Systematic review used as a source of primary papers |
| Hu, Chieh-Ying, Sun, Li-Chen, Lin, Ming-Yen et al. (2024) Validating the accuracy of the Hendrich II Fall Risk Model for hospitalized patients using the ROC curve analysis. The Kaohsiung journal of medical sciences 40(4): 404-412 | - Study does not contain an intervention relevant to this review protocol |
| Hwang, Stephanie, Hughes, Tamera D, Niznik, Joshua et al. (2024) Association of Average Daily Morphine Milligram Equivalents and Falls in Older Adult Chronic Opioid Users. Pharmacy (Basel, Switzerland) 12(2) | - Study does not contain an intervention relevant to this review protocol |
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| patients: A retrospective, cohort study. Archives of Gerontology and Geriatrics 118: 105315 | |
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| Jahandideh, S, Hutchinson, A F, Bucknall, T K et al. (2024) Using machine learning models to predict falls in hospitalised adults. International journal of medical informatics 187: 105436 | - Population not relevant to this review protocol |
| Jung, H.; Park, H.-A.; Lee, H.-Y. (2023) Impact of a Decision Support System on Fall-Prevention Nursing Practices. Journal of patient safety 19(8): 525-531 | - Population not relevant to this review protocol |
| Jung, Hyesil and Park, Hyeoun-Ae (2017) Use of EHR Data to Identify Factors Affecting the Time to Fall. Studies in health technology and informatics 245: 1043-1047 | - Population not relevant to this review protocol |
| Jung, Hyesil; Park, Hyeoun-Ae; Hwang, Hee (2020) Improving Prediction of Fall Risk Using Electronic Health Record Data With Various Types and Sources at Multiple Times. Computers, informatics, nursing : CIN 38(3): 157-164 | - Population not relevant to this review protocol |
| Jung, Hyesil, Yoo, Sooyoung, Kim, Seok et al. (2022) Patient-Level Fall Risk Prediction Using the Observational Medical Outcomes Partnership's Common Data Model: Pilot Feasibility Study. JMIR medical informatics 10(3): e35104 | - Population not relevant to this review protocol |
| Kalivas, B., Zhang, J., Harper, K. et al. (2023) The Association between Delirium and In-Hospital Falls: A Cross-Sectional Analysis of a Delirium Screening Program. Journal of Aging Research 2023: 1562773 | - Study design not relevant to this review protocol |
| Kawazoe, Yoshimasa, Shimamoto, Kiminori, Shibata, Daisaku et al. (2022) Impact of a Clinical Text-Based Fall Prediction Model on Preventing Extended Hospital Stays for Elderly Inpatients: Model Development and Performance Evaluation. JMIR medical informatics 10(7): e37913 | - Study design not relevant to this review protocol |
| Kharrazi, H., Anzaldi, L.J., Hernandez, L. et al. (2018) The Value of Unstructured Electronic Health Record Data in Geriatric Syndrome Case Identification. Journal of the American Geriatrics Society 66(8): 1499-1507 | - Data not reported in an extractable format or a format that can be analysed |
| Krakau, Karolina, Andersson, Helene, Dahlin, Asa Franzen et al. (2021) Validation of nursing documentation regarding in-hospital falls: a cohort study. BMC nursing 20(1): 58 | - Study does not contain an intervention relevant to this review protocol |
| Kwon, Eunok; Chang, Sun Ju; Kwon, Mikyung (2023) A Clinical Data Warehouse Analysis of Risk Factors for Inpatient Falls in a Tertiary Hospital: A Case-Control Study. Journal of patient safety 19(8): 501-507 | - Study design not relevant to this review protocol |
| Ladios-Martin, M., Cabanero-Martinez, M.-J., Fernandez-de-Maya, J. et al. (2022) Predictive inpatient falls risk model using Machine Learning. Journal of nursing management | - Population not relevant to this review protocol |

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| Ladios-Martin, Mireia, Cabanero-Martinez, Maria-Jose, Fernandez-de-Maya, Jose et al. (2022) Development of a predictive inpatient falls risk model using machine learning. Journal of nursing management | - Population not relevant to this review protocol |
| Larsson, G., Eldh, J., Hagman, E. et al. (2024) The non-conveyance of trauma patients in Swedish emergency medical services: a retrospective observational study of the trauma population not transported to an emergency department. BMC Emergency Medicine 24(1): 34 | - Study does not contain an intervention relevant to this review protocol |
| Lee, Ju Young, Jin, Yinji, Piao, Jinshi et al. (2016) Development and evaluation of an automated fall risk assessment system. International journal for quality in health care : journal of the International Society for Quality in Health Care 28(2): 175-82 | - Population not relevant to this review protocol |
| Li, Q., Chen, Y., Qin, D. et al. (2023) Development and validation of dynamic nomogram of frailty risk for older patients hospitalized with heart failure. International Journal of Nursing Sciences 10(2): 142-150 | - Study does not contain an intervention relevant to this review protocol |
| Lien-Chung, Wei (2024) Integrating Multifaceted Strategies to Prevent Patient Falls: Insights and Implementations at Taoyuan Psychiatric Center...Kwon E, Sun Ju Chang, Mikyung Kwon. A Clinical Data Warehouse Analysis of Risk Factors for Inpatient Falls in a Tertiary Hospital: A Case-Control Study. Journal of Patient Safety. 2023. Journal of Patient Safety 20(3): e8-e8 | - Study design not relevant to this review protocol |
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| Litzelman, Debra K., Butler, Dawn E., Iloabuchi, Tochukwu et al. (2023) Combined interprofessional education and system intervention to improve screening older adults for dementia and falls. Gerontology & Geriatrics Education 44(1): 75-87 | - Study does not contain an intervention relevant to this review protocol |
| Liu, Chia-Hui; Hu, Ya-Han; Lin, Yu-Hsiu (2021) A Machine Learning-Based Fall Risk Assessment Model for Inpatients. Computers, informatics, nursing : CIN 39(8): 450-459 | - Population not relevant to this review protocol |
| Liu, Daniel, Binkley, Neil C, Perez, Alberto et al. (2023) CT image-based biomarkers acquired by AI-based algorithms for the opportunistic prediction of falls. BJR open 5(1): 20230014 | - Study does not contain an intervention relevant to this review protocol |
| Lopez, M., Fernandez-Castro, M., Martin-Gil, B. et al. (2022) Auditing completion of nursing records as an outcome indicator for identifying patients at risk of developing pressure ulcers, falling, and social vulnerability: An observational study. Journal of nursing management 30(4): 1061-1068 | - Study design not relevant to this review protocol |
| Lucero, Robert James, Lindberg, David S, Fehlberg, Elizabeth A et al. (2019) A data-driven and practice-based approach to identify risk factors associated with hospital-acquired falls: Applying manual and semi- and fully-automated methods. International journal of medical informatics 122: 63-69 | - Population not relevant to this review protocol |

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| Luna-Aleixos, D., Llagostera-Reverter, I., Castello-Benavent, X. et al. (2023) Development and Validation of a Meta-Instrument for the Assessment of Functional Capacity, the Risk of Falls and Pressure Injuries in Adult Hospitalization Units (VALENF Instrument) (Part II). International Journal of Environmental Research and Public Health 20(6): 5003 | - Study does not contain an intervention relevant to this review protocol |
| Lytle, Kay S, Westra, Bonnie L, Whittenburg, Luann et al. (2021) Information Models Offer Value to Standardize Electronic Health Record Flowsheet Data: A Fall Prevention Exemplar. Journal of nursing scholarship : an official publication of Sigma Theta Tau International Honor Society of Nursing 53(3): 306-314 | - Study design not relevant to this review protocol |
| Mandl, L.A., Lyman, S., Quinlan, P. et al. (2013) Falls among patients who had elective orthopaedic surgery: A decade of experience from a musculoskeletal specialty hospital. Journal of Orthopaedic and Sports Physical Therapy 43(2): 91-96 | - Study design not relevant to this review protocol |
| Machado, S., Ferro, C., Tkachuk, O. et al. (2024) FALL-INCREASING RISK DRUGS (FRIDS) AND FALL-RELATED FRACTURES...European Association of Hospital Pharmacists (EAHP) 28th Congress, March 20-22, 2024, Bordeaux, France. European Journal of Hospital Pharmacy 31: a213-a213 | - Study does not contain an intervention relevant to this review protocol |
| McCart, James A, Berndt, Donald J, Jarman, Jay et al. (2013) Finding falls in ambulatory care clinical documents using statistical text mining. Journal of the American Medical Informatics Association : JAMIA 20(5): 906-14 | - Study does not contain an intervention relevant to this review protocol |
| McCarthy, B., Fitzgerald, S., O'Shea, M. et al. (2019) Electronic nursing documentation interventions to promote or improve patient safety and quality care: A systematic review. Journal of nursing management 27(3): 491-501 | - More recent systematic review included that covers the same topic |
| McCormley, Kevin; George, Elisabeth L.; Harlan, Melissa (2024) TUMBLE to Reduce Falls After Intensive Care Unit Stay. Journal of Nursing Care Quality 39(2): 102-105 | - Study does not contain an intervention relevant to this review protocol |
| Mei, Yi You, Marquard, Jenna, Jacelon, Cynthia et al. (2013) Designing and evaluating an electronic patient falls reporting system: perspectives for the implementation of health information technology in long-term residential care facilities. International journal of medical informatics 82(11): e294-306 | - Study design not relevant to this review protocol |
| Mei-Wen, Wu, Shu-Mei, Lai, Chi-Yi, Huang et al. (2023) Evaluation of the Nursing Information System and Quality Indicators Improvement: A Case Study in Taiwan from 2011 to 2022. Online Journal of Nursing Informatics 26(3): 3-3 | - Study does not contain an intervention relevant to this review protocol |
| Melzer, D., Tavakoly, B., Winder, R.E. et al. (2015) Much more medicine for the oldest old: trends in UK electronic clinical records. Age and Ageing 44(1): 46-53 | - Study does not contain an intervention relevant to this review protocol |
| Mion, Lorraine C, Chandler, A Michelle, Waters, Teresa M et al. (2012) Is it possible to identify risks for injurious falls in hospitalized patients?. Joint Commission journal on quality and patient safety 38(9): 408-13 | - Population not relevant to this review protocol |

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| Mishra, A.K., Chappell, M.J., Emerson, S. et al. (2023) Fall Risk Prediction in Older Adults Using Free-Text Nursing Notes and Medications in Electronic Health Records. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference 2023: 1-4 | - Study does not contain an intervention relevant to this review protocol |
| Moran, R., Ramirez, M., Woods, G. et al. (2023) Shared-Medical Appointment for Screening and Risk Assessment for Fall Prevention. Gerontology and Geriatric Medicine 9 | - Study does not contain an intervention relevant to this review protocol |
| Moskowitz, Gil, Egorova, Natalia N, Hazan, Ariela et al. (2020) Using Electronic Health Records to Enhance Predictions of Fall Risk in Inpatient Settings. Joint Commission journal on quality and patient safety 46(4): 199-206 | - Population not relevant to this review protocol |
| Nakatani, Hayao, Nakao, Masatoshi, Uchiyama, Hidefumi et al. (2020) Predicting Inpatient Falls Using Natural Language Processing of Nursing Records Obtained From Japanese Electronic Medical Records: Case-Control Study. JMIR medical informatics 8(4): e16970 | - Study design not relevant to this review protocol |
| NCT05390736 (2022) Evaluating the Cost Effectiveness of STEADI. https://clinicaltrials.gov/show/NCT05390736 | - Study does not contain an intervention relevant to this review protocol |
| NCT05538455 (2022) Investigating ProCare4Life Impact on Quality of Life of Elderly Subjects With Neurodegenerative Diseases. https://clinicaltrials.gov/show/NCT05538455 | - Study does not contain an intervention relevant to this review protocol |
| Nguyen, H.T.; Nguyen, C.C.; Hoang, T.L. (2022) Falls Among Older Adults During the COVID-19 Pandemic: A Multicenter Cross-Sectional Study in Vietnam. Clinical Interventions in Aging 17: 1393-1404 | - Study design not relevant to this review protocol |
| Nicholson, H., Voss, S., Black, S. et al. (2022) Factors influencing conveyance of older adults with minor head injury by paramedics to the emergency department: a multiple methods study. BMC Emergency Medicine 22(1): 184 | - Study does not contain an intervention relevant to this review protocol |
| Nothelle, Stephanie K, McGuire, Maura, Boyd, Cynthia M et al. (2022) Effects of screening for geriatric conditions and advance care planning at the Medicare Annual Wellness Visit. Journal of the American Geriatrics Society 70(2): 579-584 | - Study does not contain an intervention relevant to this review protocol |
| Ortenzio, Mark P, Brittain, Garrett V, Frommeyer, Timothy C et al. (2024) Quality evaluation of the usefulness of an emergency department fall risk assessment tool. The American journal of emergency medicine 76: 93-98 | - Study does not contain an intervention relevant to this review protocol |
| Oshiro, C.E.S., Frankland, T.B., Rosales, A.G. et al. (2019) Fall Ascertainment and Development of a Risk Prediction Model Using Electronic Medical Records. Journal of the American Geriatrics Society | - Population not relevant to this review protocol |
| Parsons, Rex, Blythe, Robin D, Cramb, Susanna M et al. (2022) Inpatient Fall Prediction Models: A Scoping Review. Gerontology: 1-16 | - Systematic review used as source of primary studies |

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| Patterson, B.W., Smith, M.A., Repplinger, M.D. et al. (2017) Using Chief Complaint in Addition to Diagnosis Codes to Identify Falls in the Emergency Department. Journal of the American Geriatrics Society 65(9): e135-e140 | - Study design not relevant to this review protocol |
| Patterson, B.W., Repplinger, M.D., Pulia, M.S. et al. (2018) Using the Hendrich II Inpatient Fall Risk Screen to Predict Outpatient Falls After Emergency Department Visits. Journal of the American Geriatrics Society 66(4): 760-765 | - Study does not contain an intervention relevant to this review protocol |
| Patterson, Brian W, Jacobsohn, Gwen C, Shah, Manish N et al. (2019) Development and validation of a pragmatic natural language processing approach to identifying falls in older adults in the emergency department. BMC medical informatics and decision making 19(1): 138 | - Study does not contain an intervention relevant to this review protocol |
| Pavon, J.M., Previll, L., Woo, M. et al. (2023) Machine learning functional impairment classification with electronic health record data. Journal of the American Geriatrics Society 71(9): 2822-2833 | - Study does not contain an intervention relevant to this review protocol |
| Persell, S.D., Brown, T., Doctor, J.N. et al. (2022) Development of High-Risk Geriatric Polypharmacy Electronic Clinical Quality Measures and a Pilot Test of EHR Nudges Based on These Measures. Journal of General Internal Medicine 37(11): 2777-2785 | - Study does not contain an intervention relevant to this review protocol |
| Pham, C.T., Visvanathan, R., Strong, M. et al. (2023) Cost-Effectiveness and Value of Information Analysis of an Ambient Intelligent Geriatric Management (AmbIGeM) System Compared to Usual Care to Prevent Falls in Older People in Hospitals. Applied Health Economics and Health Policy 21(2): 315-325 | - Study does not contain an intervention relevant to this review protocol |
| Podesser, Franziska, Weninger, Johannes, Weiss, Elisabeth M et al. (2024) Short-term Medication Effect on Fall Risk in Multimorbid Inpatients with Dementia. Gerontology | - Study does not contain an intervention relevant to this review protocol |
| Pujades-Rodriguez, Mar, Assi, Valentina, Gonzalez-Izquierdo, Arturo et al. (2018) The diagnosis, burden and prognosis of dementia: A record-linkage cohort study in England. PloS one 13(6): e0199026 | - Population not relevant to this review protocol |
| Quinlan, Sharon and Ryer, Suzanne (2023) Implementing a Fall Prevention Initiative in Nurse-Facilitated Annual Wellness Visits: A Quality Improvement Project. Journal of Nursing Care Quality 38(3): 243-250 | - Study does not contain an intervention relevant to this review protocol |
| Rio, Tatiane Goncalves Gomes de Novais do, Nogueira, Lilia de Souza, Lima, Fernanda Rodrigues et al. (2023) Performance of severity indices for admission and mortality of trauma patients in the intensive care unit: a retrospective cohort study. European journal of medical research 28(1): 559 | - Study does not contain an intervention relevant to this review protocol |
| Ritchey, K., Olney, A., Chen, S. et al. (2022) STEADI Self-Report Measures Independently Predict Fall Risk. Gerontology and Geriatric Medicine 8 | - Study does not contain an intervention relevant to this review protocol |
| Ruzic-Gorenjec, Nina, Klemenc Ketis, Zalika, Blagus, Rok et al. (2023) Fall Risk in Adult Family Practice Non-Attenders: A Cross-Sectional Study from Slovenia. Zdravstveno varstvo 62(2): 76-86 | - Study design not relevant to this review protocol |

| Study | Code [Reason] |
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| Saxena, S., Meldon, S., Hashmi, A.Z. et al. (2023) Use of the electronic medical record to screen for high-risk geriatric patients in the emergency department. JAMIA Open 6(2): ooad021 | - Study does not contain an intervention relevant to this review protocol |
| Schell, Kathleen; Lyons, Denise; Bodt, Barry (2023) Orthostatic Hypotension and Falls: An Inpatient Comparison. MEDSURG Nursing 32(5): 322-332 | - Study does not contain an intervention relevant to this review protocol |
| Seaman, K., Ludlow, K., Wabe, N. et al. (2022) The use of predictive fall models for older adults receiving aged care, using routinely collected electronic health record data: a systematic review. BMC geriatrics 22(1): 210 | - Systematic review used as source of primary studies |
| Shear, K., Rice, H., Garabedian, P.M. et al. (2023) Management of Fall Risk Among Older Adults in Diverse Primary Care Settings. Journal of Applied Gerontology 42(11): 2219-2232 | - Study does not contain an intervention relevant to this review protocol |
| Shear, K., Rice, H., Garabedian, P.M. et al. (2023) Usability Testing of an Interoperable Computerized Clinical Decision Support Tool for Fall Risk Management in Primary Care. Applied clinical informatics 14(2): 212-226 | - Study does not contain an intervention relevant to this review protocol |
| Sheppard, J.P., Koshiaris, C., Stevens, R. et al. (2023) The association between antihypertensive treatment and serious adverse events by age and frailty: A cohort study. PLoS Medicine 20(4): e1004223 | - Study does not contain an intervention relevant to this review protocol |
| Shim, Soyun, Yu, Jae Yong, Jekal, Seyong et al. (2022) Development and Validation of Interpretable Machine Learning Models for Inpatient Fall Events and EMR Integration. Clinical and experimental emergency medicine | - Population not relevant to this review protocol |
| Shin, J.-W., Park, H.J., Park, Y. et al. (2024) Risk Factors and Characteristics of In-Hospital Falls after Spine Surgery: A Retrospective, Single-Center Cohort Study in the Republic of Korea. JBJS Open Access 9(2): e2300096 | - Study does not contain an intervention relevant to this review protocol |
| Shiner, B., Neily, J., Mills, P.D. et al. (2020) Identification of Inpatient Falls Using Automated Review of Text-Based Medical Records. Journal of patient safety 16(3): e174-e178 | - Population not relevant to this review protocol |
| Song, Wenyu, Latham, Nancy K, Liu, Luwei et al. (2024) Improved accuracy and efficiency of primary care fall risk screening of older adults using a machine learning approach. Journal of the American Geriatrics Society 72(4): 1145-1154 | - Study design not relevant to this review protocol |
| Spears, Gwendolyn V, Roth, Carol P, Miake-Lye, Isomi M et al. (2013) Redesign of an electronic clinical reminder to prevent falls in older adults. Medical care 51(3suppl1): 37-43 | - Study does not contain an intervention relevant to this review protocol |
| Tamblyn, R., Eguale, T., Buckeridge, D. L., Huang, A., Hanley, J., Reidel, K., Shi, S., & Winslade N. (2012). The effectiveness of a new generation of computerized drug alerts in reducing the risk of injury from drug side effects: A cluster randomized trial. Journal of the American Medical Informatics Association. 19(4) 635-643. | - Study design not relevant to this review protocol |

| Study | Code [Reason] |
|---|---|
| Tanaka, Shinya, Imaizumi, Takahiro, Morohashi, Akemi et al. (2023) In-Hospital Fall Risk Prediction by Objective Measurement of Lower Extremity Function in a High-Risk Population. Journal of the American Medical Directors Association 24(12): 1861-1867e2 | - Study does not contain an intervention relevant to this review protocol |
| Tebe, C., Pallares, N., Reyes, C. et al. (2022) Development and external validation of a 1- and 5-year fracture prediction tool based on electronic medical records data: The EPIC risk algorithm. Bone 162: 116469 | - Population not relevant to this review protocol |
| Tohira, Hideo, Finn, Judith, Ball, Stephen et al. (2022) Machine learning and natural language processing to identify falls in electronic patient care records from ambulance attendances. Informatics for health & social care 47(4): 403-413 | - Population not relevant to this review protocol |
| Toyabe, S. (2012) Detecting inpatient falls by using natural language processing of electronic medical records. BMC health services research 12: 448 | - Study does not contain an intervention relevant to this review protocol |
| Troncoso-Marino, Amelia, Roso-Llorach, Albert, Lopez-Jimenez, Tomas et al. (2021) Medication-Related Problems in Older People with Multimorbidity in Catalonia: A Real-World Data Study with 5 Years' Follow-Up. Journal of clinical medicine 10(4) | - Study does not contain an intervention relevant to this review protocol |
| Ude-Okeleke, Rosetta Chinyere, Aslanpour, Zoe, Dhillon, Soraya et al. (2024) Types, predictors, and consequences of medicines related problems (MRPs) in frail older adults admitted to hospital from primary care - A retrospective cohort study. Exploratory research in clinical and social pharmacy 13: 100402 | - Study does not contain an intervention relevant to this review protocol |
| Verma, V., Dawar, V., Bhargava, S. et al. (2023) RWD151 A Machine Learning Approach to Predict the Risk of Fall for Elderly Patients Using Physiological Attributes from the Market Clarity Database. Value in Health 26(6supplement): 390 | - Conference abstract |
| Vincenzo, Jennifer L, Caulley, Jamie, Scott, Aaron J et al. (2024) Integrating STEADI for Falls Prevention in Outpatient Rehabilitation Clinics: An Outcomes Evaluation Using the RE-AIM Framework. Gerontologist 64(4): 1-12 | - Study does not contain an intervention relevant to this review protocol |
| Vu, Trang; Day, Lesley; Finch, Caroline F (2012) Linked versus unlinked hospital discharge data on hip fractures for estimating incidence and comorbidity profiles. BMC medical research methodology 12: 113 | - Study does not contain an intervention relevant to this review protocol |
| Wabe, Nasir, Meulenbroeks, Isabelle, Huang, Guogui et al. (2024) Development and internal validation of a dynamic fall risk prediction and monitoring tool in aged care using routinely collected electronic health data: a landmarking approach. Journal of the American Medical Informatics Association : JAMIA 31(5): 1113-1125 | - Study does not contain an intervention relevant to this review protocol |
| Wang, Ya-ping, Dai, Can, Ou-yang, Ping et al. (2024) Evaluation of a concise fall risk stratification among older adults with cataracts in day surgery settings: A historically controlled study. Japan Journal of Nursing Science 21(2): 1-9 | - Study does not contain an intervention relevant to this review protocol |
| Watkins, Paige M, Hill, Anne-Marie, Tohira, Hideo et al. (2023) Epidemiology of ambulance-attended adults who fell in Western Australia 2015 - 2021: An increasing incidence in an ageing population. Injury 54(12): 111035 | - Study does not contain an intervention relevant to this review protocol |

| Study | Code [Reason] |
|---|---|
| Weber, V., White, A., McIlvried, R. (2008) An electronic medical record (EMR)-based intervention to reduce polypharmacy and falls in an ambulatory rural elderly population. Journal of General Internal Medicine. 23(4) 399-404 | - Study design not relevant to this review protocol |
| Weed-Pfaff, Samantha H, Nutter, Benjamin, Bena, James F et al. (2016) Validation of Predictors of Fall Events in Hospitalized Patients With Cancer. Clinical journal of oncology nursing 20(5): e126-31 | - Population not relevant to this review protocol |
| Williams, J.R., Muesch, A.J., Svenson, J.E. et al. (2022) Utility of bedside assessment to evaluate for cervical-spine fracture post ground-level fall for patients 65 years and older. American Journal of Emergency Medicine 53: 208-214 | - Study does not contain an intervention relevant to this review protocol |
| Womack, J.A.; Garla, V.; Brandt, C.A. (2013) Identifying falls in an EHR-based cohort. Clinical and Translational Science 6(2): 122 | - Conference abstract |
| Wong, Ho Lun, Weaver, Claire, Marsh, Lauren et al. (2023) Polypharmacy and cumulative anticholinergic burden in older adults hospitalized with fall. Aging medicine (Milton (N.S.W)) 6(2): 116-123 | - Study does not contain an intervention relevant to this review protocol |
| Wright, J.R., D'Ausilio, J., Holmberg, J.M. et al. (2023) Using Quality Indicator Codes to Identify Patients' Fall Risk in Inpatient Rehabilitation Facilities. Archives of Physical Medicine and Rehabilitation 104(9): 1394-1401 | - Study does not contain an intervention relevant to this review protocol |
| Wu, M.-W., Lee, T.-T., Lai, S.-M. et al. (2019) Evaluation of Electronic Health Records on the Nursing Process and Patient Outcomes Regarding Fall and Pressure Injuries. Computers, informatics, nursing : CIN 37(11): 573-582 | - Population not relevant to this review protocol |
| Yokota, S., Tomotaki, A., Mohri, O. et al. (2018) Evaluating the Effectiveness of a Fall Risk Screening Tool Implemented in an Electronic Medical Record System. Journal of nursing care quality 33(4): e1-e6 | - Population not relevant to this review protocol |
| Yokota, Shinichiroh; Endo, Miyoko; Ohe, Kazuhiko (2017) Establishing a Classification System for High Fall-Risk Among Inpatients Using Support Vector Machines. Computers, informatics, nursing : CIN 35(8): 408-416 | - Population not relevant to this review protocol |
| Yokota, Shinichiroh and Ohe, Kazuhiko (2016) Construction and evaluation of FiND, a fall risk prediction model of inpatients from nursing data. Japan journal of nursing science : JJNS 13(2): 247-55 | - Population not relevant to this review protocol |
| Yokota, Shinichiroh, Tomotaki, Ai, Mohri, Ohmi et al. (2016) Evaluation of a Fall Risk Prediction Tool Using Large-Scale Data. Studies in health technology and informatics 225: 800-1 | - Data not reported in an extractable format or a format that can be analysed |
| Yusupov, E.; Chen, D.; Krishnamachari, B. (2017) Medication use and falls: Applying Beers criteria to medication review in Parkinson's disease. SAGE Open Medicine 5 | - Study design not relevant to this review protocol |
| Zeneli, Anita, Montalti, Sandra, Masciangelo, Itria et al. (2022) Fall predictors in hospitalized patients living with cancer: a case-control study. Supportive care in cancer : official journal of the Multinational Association of Supportive Care in Cancer 30(10): 7835-7843 | - Study design not relevant to this review protocol |

| Study | Code [Reason] |
|---|---|
| Zhu, Vivienne J, Walker, Tina D, Warren, Robert W et al. (2017) Identifying Falls Risk Screenings Not Documented with Administrative Codes Using Natural Language Processing. AMIA ... Annual Symposium proceedings. AMIA Symposium 2017: 1923-1930 | - Study does not contain an intervention relevant to this review protocol |

## J.2 Health Economic studies

Published health economic studies that met the inclusion criteria (relevant population, comparators, economic study design, published 2007 or later and not from non-OECD country or USA) but that were excluded following appraisal of applicability and methodological quality are listed below. See the health economic protocol for more details.

**Table 26: Studies excluded from the health economic review**

| Reference | Reason for exclusion |
|---|---|
| None | |