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ORIGINAL ARTICLE

Falls in the elderly were predicted opportunistically using a decision tree and systematically using a database-driven screening tool

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Abstract

Objective: To identify risk factors for falls and generate two screening tools: an opportunistic tool for use in consultation to flag at risk patients and a systematic database screening tool for comprehensive falls assessment of the practice population.

Study Design and Setting: This multicenter cohort study was part of the quality improvement in chronic kidney disease trial. Routine data for participants aged 65 years and above were collected from 127 general practice (GP) databases across the UK, including sociodemographic, physical, diagnostic, pharmaceutical, lifestyle factors, and records of falls or fractures over 5 years. Multilevel logistic regression analyses were performed to identify predictors. The strongest predictors were used to generate a decision tree and risk score.

Results: Of the 135,433 individuals included, 10,766 (8%) experienced a fall or fracture during follow-up. Age, female sex, previous fall, nocturia, anti-depressant use, and urinary incontinence were the strongest predictors from our risk profile (area under the receiver operating characteristics curve = 0.72). Medication for hypertension did not increase the falls risk. Females aged over 75 years and subjects with a previous fall were the highest risk groups from the decision tree. The risk profile was converted into a risk score (range −7 to 56). Using a cut-off of ≥9, sensitivity was 68%, and specificity was 60%.

Conclusion: Our study developed opportunistic and systematic tools to predict falls without additional mobility assessments. © 2014 Elsevier Inc. All rights reserved.

Keywords: Falls risk; Fractures; Elderly; Screening tool; General practice; Medical records systems; Computerised

1. Introduction

Falls are the leading cause of injury in individuals aged over 65 years [1]. A total of 30% of this population will experience a fall each year [2−5], with the total number steadily increasing as the elderly population grows [6]. They are a cause of substantial physical and psychological morbidity, with 10% of falls resulting in a major injury [5,7], 5% resulting in a fracture [5,7,8], and many elderly individuals being left with a residual fear of falling leading to social isolation [9−11], increased dependence, and institutionalization [7,12,13]. Falls are a considerable public health burden with an estimated annual cost to the National Health Service (NHS) of £1.7 billion [14].

Falls prevention services have been shown to reduce the risk of falls by up to 55% [15], and reviews have shown that interventions to prevent falls can be cost saving [16]. Limitations on health-care resources mean that it is not possible to offer these services to all patients. There is therefore a need for an accurate risk assessment tool that can be easily implemented to identify which individuals are at highest risk of falling and would most benefit from referral to these services.

Disclosures: S.de.L. led the expert reference group for the development of the quality and outcomes framework (QOF) chronic kidney disease (CKD) indicator. A pay-for-performance chronic disease management program. Subsequently lead author for NHS Employers/British Medical Association frequently asked questions (FAQs) about CKD, now in its third edition; and General Practitioner Advisor to NICE for CKD indicator. Funding to write three articles and give two invited conference lectures in last 5 years.

H.G. was an expert advisor to QOF, co-author CKD FAQs, honoraria for lectures to General Practitioners. K.H. co-authored for NHS Employers/British Medical Association FAQs about CKD, now in its third edition; Member of NICE CKD clinical guideline develop group; Honoraria received for lectures to General Practitioners on CKD. The remaining authors declared no competing interests.

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What is new?

Key finding

- This study adds evidence for nocturia and urinary incontinence to known predictors of falls: age, female sex, previous falls, and anti-depressants.
- Increased age, female sex, previous fall, nocturia, anti-depressant use, and urinary incontinence were the strongest predictors of falls from our risk profile.

What this study adds to what was known?

- Individuals at high risk of falls can be identified opportunistically from routinely collected GP data without requiring face-to-face functional mobility assessments.
- A systematic database-driven screening tool has been created, with the potential for incorporation into existing GP electronic systems, to allow automated screening of practice populations to flag-up high-risk individuals.

What is the implication and what should change now?

- Opportunistic and systematic assessment tools have been developed based on risk factors, and after validation in a large population, they could be readily implemented as screening tools in primary care.
- These tools can be used as part of routine fall assessments to guide referrals to fall prevention services.

There are a number of epidemiologic studies on risk factors for falls, with use of sedative medications, previous falls, dizziness, and poor performance on balance assessments being among the strongest predictors [4,14,17,18]. Based on these findings, a number of falls risk screening tools have been developed [4,7,12,18−22]. These are either purely functional mobility assessments (FMAs) of gait, strength, and balance or an FMA combined with other risk factors to generate a multi-factorial assessment (MFA) tool for falls. FMAs can provide important information on the physical attributes of individuals, which may predispose them to falls, but these measures are time consuming, subjective, and cannot be easily carried out across a population as part of a screening tool in the community-dwelling elderly. Additionally, the information is not readily available from routinely collected general practice (GP) data, and the predictors used to form the basis of the existing falls risk assessments have been identified from relatively small populations with great variation in risk factors found to be significant contributors to falls between the studies described in the literature. There is no stand-alone MFA tool based on risk factors derived from a large population that can be easily implemented as a screening tool in primary care.

We carried out this large cohort study to identify significant risk factors for falls in the elderly, with specific attention to the impact of blood pressure and use of antihypertensive medication on occurrence of falls, as set out by the quality improvement in chronic kidney disease (QICKD) trial protocol [23]. From these findings, we aim to develop two screening tools based on routinely collected GP data. Screening in family practice can be either opportunistic, carried out when the patient presents; or systematic, involving methodical searching of practice data and recalling patients who meet the eligibility criteria for the given screening process. We, therefore, developed tools that might be used in either of these ways: a quick, simple visual aid for opportunistic case identification during GP consultations in all elderly patients, completed using information already available to the GP's from previous and current consultations, and a comprehensive GP database screening tool for integration into existing computerized medical record systems to systematically flag up individuals at high risk of falls who may benefit from falls prevention services. Use of computerized prompts has become a routine element of GP consultations [24]. Two distinct tools will be developed as it appears from studying other disease areas, such as atrial fibrillation [25], that both opportunistic and systematic approaches to case finding have a role in primary care.

2. Methods

2.1. Study population

Data for this study were collected as part of the QICKD randomized cluster trial using routinely collected information from 127 GP databases across the UK [23,26]. The initial trial data set comprised a comprehensive set of 11,541 variables relating to cardiovascular disease, risk and management. The sampling and data collection protocols for the QICKD trial have been previously described in detail [23]. As data were extracted for the whole practice population in the QICKD trial to identify people with chronic kidney disease (CKD), there were no exclusions that might have resulted in selection bias being applied. A sub-sample of the QICKD population was selected for use in this study based on the eligibility criteria of participants being aged 65 years or above as of June 1, 2008, the end point of the initial data collection period. A total of 135,433 individuals were identified from the parent population of 965,782 patients and were subsequently included in this study. Data collection was performed over a 5-year period between January 2006 and December 2010; data collected during the first 30 months were used to determine

the baseline characteristics of the population, and data collected in the subsequent 30 months were used to obtain follow-up information.

2.2. Data collection

General practices in the UK use a standardized coding system to record clinical information based on the NHS Read codes [27,28]. Information is collected and coded during each clinical encounter and stored on the main GP database for the practice. We used the NHS Browser database to identify coding lists for each of the variables considered to be potential predictors for falls, based on the existing literature [14,17,18]. These codes were extracted from the 127 participating GP databases during the 30-month observation period as part of the QICKD trial.

2.2.1. Predictors

Five categories of potential predictors for falls were identified for inclusion in this study: socio-demographic, physical, diagnostic, pharmaceutical, and lifestyle factors. The specific predictors included in each category were determined based on evidence from the existing literature and variables extracted as part of the QICKD trial that were considered reasonable potential predictors for falls.

Sociodemographic characteristics included age at the end of the initial data collection period, gender, presence of a carer, and the index of multiple deprivation score, determined by the geographical area participants lived in. Physical measurements included body mass index (BMI), with subjects being classified according to categories defined by the WHO criteria (<18.5 = low BMI, $18.5-25$ = normal BMI, >25 = high BMI); systolic blood pressure (BP) and reduced foot sensation, determined by an abnormal result on a monofilament test for peripheral neuropathy. Medical conditions that have been previously linked to increased falls were considered for inclusion in this study, specifically urinary incontinence [12,29], dizziness [12,20], lower limb osteoarthritis (OA) [19], and stroke [4,18]. These factors were extended to include nocturia, other forms of cardiovascular disease, diabetes, CKD, and anemia. A number of medications have been associated with falls in existing studies. The strongest evidence is for sedative medications, but links have been suggested with anti-depressants, anti-psychotics, anti-epileptics, digoxin, calcium channel blockers, anti-inflammatories, and medication for hypertension [5,12,14,30]. This study focused on sedative medications and anti-depressants. Given the previously identified correlation between cardiovascular disease and orthostatic hypotension with falls [4,18], it extended this group to include anti-hypertensives and medications commonly prescribed for secondary prevention of cardiovascular disease, aspirin, and lipid-lowering therapy. Lifestyle factors considered included alcohol consumption, classed as excessive if greater than 21 units per week; smoking status at the end of observation period and occurrence of a previous fall or falls (>1) during the 30-month observation period. Details of the specific variables extracted are shown in Table 1. For ease of clinical interpretation, all continuous variables were categorized before being entered into the statistical analysis. These categories were based either on established clinical cut-off points or, if no such cut-off point existed, according to deciles or regular intervals (see Table 1 for details). As absence of a diagnosis is not recorded in GP databases, if a patient was not coded to have a condition they were assumed not to have it. In the case of variables where a negative response could be recorded, for example 'non-smoker', then the option of 'missing' was used if no information was recorded. The introduction of "Pay for Performance" (P4P) in 2004 in UK primary care has improved the recording of chronic disease. Most key cardiovascular diagnoses are included in the P4P framework.

2.2.2. Definition of cases/outcome

The outcome measure used in this study was the occurrence of either a fall or a fracture or both in the 30-month follow-up period, determined by documentation of codes for these outcomes in the GP databases. Fractures were considered alongside falls as a primary outcome measure in this study as 90% of fractures occur as a result of a fall [5,31], and this number is likely to be even higher in a purely elderly population.

2.3. Statistical analysis

Multilevel backward stepwise logistical regression was carried out on our data set to determine predictors for falls. A multilevel analysis was used to adjust for any variation between the GP practices in our population. Variables were sequentially removed from the model based on the strength of the association and impact on the Bayesian information criterion value; only variables with a statistically significant association ($P \leq 0.05$) were included in the final risk profile model. Odds ratios (ORs) with 95% confidence intervals were calculated for each of the variables included in the final risk profile model (Table 1). The predictive accuracy of the model was determined using the area under the receiver operating characteristics (ROCs) curve (AUC). Further validation studies were also carried out, including the Hosmer–Lemeshow test for goodness-of-fit across different sub-populations and collinearity studies to exclude any correlation between variables.

2.4. Decision tree model

The strongest predictors from the risk factor model were incorporated into a tree-type algorithm to produce a decision tree for identifying groups at highest risk of future falls. Decision trees can be used to convert a complex decision-making process, based on varying influences of different factors, into a collection of simpler decisions that are followed in a stepwise manner to reach a final conclusion

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Table 1. Prevalence, odds ratios (ORs), and 95% confidence intervals (CIs) for potential predictors of falls or fractures (n = 135,433)

Predictor	Prevalence (%)	OR	95% CI	*P* value
Sociodemographic				
Age ≥ 80	29	2.03	1.92, 2.15	<0.0001
Female sex	56	1.93	1.84, 2.03	<0.0001
IMD score 6th–10th decile	37	1.01	0.98, 1.05	0.7
Presence of carer	1	1.03	0.93, 1.15	0.7
Physical health				
BMI < 18.5	2	1.11	1.02, 1.21	0.2
Systolic BP < 120 mm Hg	9	1.04	0.99, 1.09	0.4
Abnormal foot sensation	1	1.11	1.01, 1.23	0.2
Medication use				
ACE inhibitors	39	0.97	0.95, 1.00	0.3
Other anti-hypertensives	26	0.93	0.91, 0.96	0.02
Sedative medications	2	1.24	1.13, 1.35	0.002
Tricyclic anti-depressant	2	1.41	1.28, 1.55	<0.0001
Other anti-depressant	2	1.53	1.37, 1.70	<0.0001
NSAIDs	12	0.99	0.95, 1.03	0.8
Aspirin	18	1.00	0.97, 1.03	0.9
Lipid-lowering drugs (statin or fibrate)	40	0.98	0.95, 1.01	0.5
Chronic disease				
Stroke	4	1.25	1.18, 1.32	<0.0001
TIA	4	1.13	1.08, 1.20	0.007
IHD (excluding MI)	15	1.16	1.11, 1.21	0.0001
Diabetes	15	1.03	0.99, 1.07	0.4
CHF	4	0.98	0.94, 1.04	0.8
MI	4	0.86	0.82, 0.90	0.01
Coronary artery disease	5	1.13	0.97, 1.32	0.4
Coronary artery operation	5	0.91	0.80, 1.03	0.5
Anemic	10	1.13	1.09, 1.18	0.0006
Urinary incontinence	2	1.45	1.33, 1.59	<0.0001
Nocturia	1	1.57	1.36, 1.82	<0.0001
Lower limb OA	2	1.18	1.09, 1.28	0.01
Dizziness	1	1.17	1.04, 1.32	0.1
CKD stage 1–2	5	1.14	1.08, 1.21	0.008
Lifestyle				
Excess alcohol consumption	4	1.13	1.05, 1.22	0.05
Current smoker	14	1.11	1.06, 1.15	0.004
Previous fall	4	1.75	1.59, 1.91	<0.0001
Recurrent fall	2	1.27	1.15, 1.40	0.002

Abbreviations: ACE, angiotensin-converting enzyme; BMI, body mass index; BP, blood pressure; CHF, congestive heart failure; CI, confidence interval; CKD, chronic kidney disease; IHD, ischemic heart disease; IMD, index of multiple deprivation; MI, myocardial infarction; NSAIDs, non-steroidal anti-inflammatory drugs; OA, osteoarthritis; OR, odds ratio; TIA, transient ischemic attack.

[32]. The tree was constructed from a central root with recursive partitioning to generate branches (nodes) based on the predictor variable-split combination with the greatest predictive power at each stage [33,34]. This process was repeated until the tree reached its terminal outputs (leaves). The tree model was pruned to varying degrees to alter the complexity of the final structure. We chose the most simplified tree to facilitate easier clinical application and interpretation. Calculations of sensitivity, specificity, and predictive accuracy were made to confirm the validity of the model.

2.5. Risk score

The risk model was also translated into a risk scoring system, which can be applied to GP databases to identify patients in the practice population who may benefit from referral to falls prevention services. To calculate this score, the regression coefficients for the predictors in the final logistic regression model were multiplied by 10 and rounded off to the nearest integer to generate a simple score for each variable, which could be added up to give a total risk score. The estimated risk for each total risk score was calculated from the logistic regression equation. Sensitivity, specificity, positive (PPV), and negative predictive values (NPVs) were calculated for each total score to determine the most appropriate cut-off point. All statistical analyses were performed using the software packages SPSS version 20 (SPSS Inc., Chicago, IL, USA) and R Version 2.15.2 (The R Foundation for Statistical Computing).

2.6. Ethics

The QICKD trial was approved by the Oxford Research Ethics Committee. Details of the ethical approval are contained in the trial registration (Current Controlled Trials reference: ISRCTN56023731. URL: http://www.

controlled-trials.com/ISRCTN56023731) [26]. All data were anonymised to ensure no patient identifiable data were used in this study.

3. Results

3.1. Study population

Data were collected on 135,433 individuals over a 5-year period. The sample consisted of 59,527 men (44%) and 75,906 women (56%), with a mean age of 75.4 years (standard deviation, 7.6; median, 74; range, 65−104 years). During the follow-up period, 10,766 participants (8%) presented to their GP with either a fall (6,889) or a fracture (4,763) or both (886).

3.2. Risk factors

Presence of a carer, dizziness, use of anti-inflammatory medications, excessive alcohol consumption, reduced foot sensation, heart failure, coronary artery disease, diabetes, and low BMI were not significantly associated with falls or fractures in this study. A total of 39% of the study population were on an angiotensin-converting enzyme (ACE) inhibitor, and 7% had a systolic BP < 120 mm Hg. No association was found between either of these factors and falls or fractures. Table 1 shows the association between each of the measured variables with the occurrence of a fall or fracture. A regression analysis of the variables was performed, with non-significant variables excluded, to generate the final risk profile model (Table 2).

Increased age, female sex, previous falls, nocturia, urinary incontinence and use of non-tricyclic anti-depressants were the six strongest predictors of future falls or fractures. Recurrent falls, sedative medications, tricyclic anti-depressants, stroke, transient ischemic attack, lower limb OA, ischemic heart disease, BMI, CKD, anemia, and smoking were also found to be significant predictors and included in the final-risk model. Interestingly, a history of a myocardial infarction or use of anti-hypertensive medications (excluding ACE inhibitors) was associated with a significant decrease in the risk of falls and fractures (Table 2). The validity of the risk model was assessed using the ROC curve for predictive accuracy, which showed an AUC of 0.720; the Hosmer−Lemeshow plot for goodness-of-fit, which indicated a well-calibrated model for the data; and tests for collinearity, which confirmed there was no correlation between any of the variables.

3.3. Decision tree for opportunistic screening

The eight strongest predictors of falls or fractures, with an OR of 1.3 or greater, were selected from the risk profile model and inserted into a tree-type algorithm. The decision tree was pruned to produce the simplest output for ease of interpretation. The final decision tree for identifying groups of individuals at highest risk of falls or fractures is shown in Fig. 1. This tree shows that individuals at higher risk of falls or fractures are those with any previous fall in the last 30 months and females aged 75 years and over who have not had a previous fall. This classification tree identifies a subgroup of the population consisting of 42,292 people of 135,433 (38.5%) who are at high risk of falls and fractures. When applied to our study population, it correctly identifies 5,720 of 10,766 individuals who went on to have a fall or fracture in the follow-up period. This sensitivity for this model is 53%; the specificity is 71%; and the positive predictive value is 14%.

Table 2. Risk profile model for occurrence of falls or fractures, obtained by multiple logistic regression (n = 135,433)

Predictor	Regression coefficient	OR (95% CI)	Risk score
Age			
65−70	reference	1	0
70−75	0.27	1.3 (1.2, 1.3)	3
75−80	0.61	1.8 (1.7, 2.0)	6
80−85	0.92	2.5 (2.3, 2.7)	9
85−90	1.17	3.2 (2.9, 3.6)	12
90−95	1.16	3.2 (2.7, 3.8)	12
95−100	1.05	2.8 (2.2, 3.6)	10
>100	1.05	2.9 (1.4, 5.4)	10
Female sex	0.69	2.0 (1.9, 2.1)	7
Previous fall	0.57	1.8 (1.6, 1.9)	6
Nocturia	0.46	1.6 (1.4, 1.8)	5
Urine incontinence	0.39	1.5 (1.4, 1.6)	4
Other anti-depressants	0.41	1.5 (1.4, 1.7)	4
Tricyclic anti-depressants	0.34	1.4 (1.3, 1.5)	3
Sedative medications	0.26	1.3 (1.2, 1.4)	3
Recurrent falls	0.25	1.3 (1.2, 1.4)	2
Stroke	0.22	1.2 (1.2, 1.3)	2
Lower limb OA	0.17	1.2 (1.1, 1.3)	2
IHD (excluding MI)	0.15	1.2 (1.1, 1.2)	1
TIA	0.12	1.1 (1.1, 1.2)	1
Smoking status			
Non-smoker	reference	1	0
Ex-smoker	0.06	1.1 (1.0, 1.1)	1
Current smoker	0.12	1.1 (1.1, 1.2)	1
MI	−0.13	0.9 (0.8, 0.9)	−1
Other anti-hypertensives	−0.07	0.9 (0.9, 1.0)	−1
Hemoglobin			
Normal range	reference	1	0
Not recorded	−0.27	0.8 (0.7, 0.8)	−3
Polycythemic	−0.17	0.8 (0.7, 1.0)	−2
Anemic	0.15	1.2 (1.1, 1.2)	2
CKD stage			
No CKD	reference	1	0
Not recorded	−0.19	0.8 (0.8, 0.8)	−2
Stage 1−2	0.13	1.1 (1.1, 1.2)	1
Stage 3−5	−0.13	0.9 (0.9, 0.9)	−1
Stage 3−5 + p	−0.03	1.0 (0.9, 1.0)	0

Abbreviations: CI, confidence interval; CKD, chronic kidney disease; IHD, ischemic heart disease; MI, myocardial infarction; OA, osteoarthritis; OR, odds ratio; TIA, transient ischemic attack.

3.4. Risk score for systematic screening

To facilitate easier clinical application and interpretation, the regression coefficients of the predictors in the final

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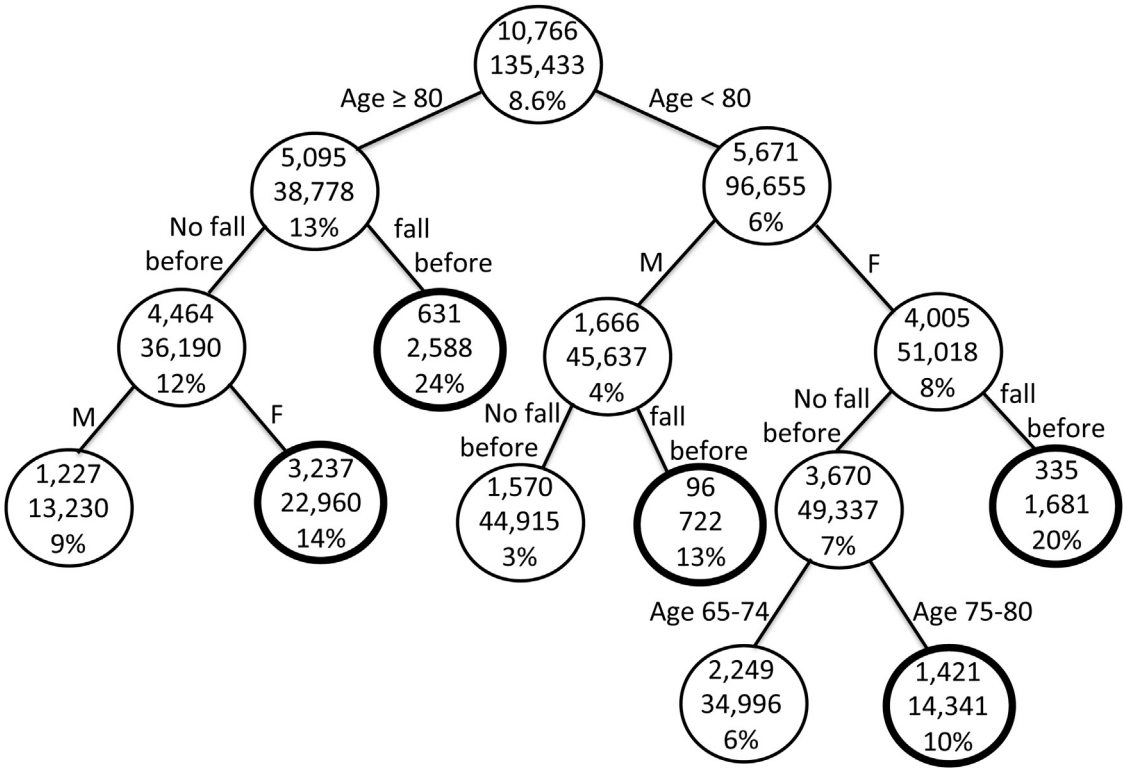

Fig. 1. Decision tree of risk factors for falls or fractures. For each category (circle), the top number is the individuals in the group who experienced a fall, the middle number is the group size, and the bottom number is the percentage of fallers in each group. The circles with thicker outlines represent high-risk end points with a falls risk ≥10%. M, male, F, female.

risk model were converted into integer values, using the methods described previously, to produce components of a risk scoring system (Table 2). The total score of our screening tool ranged from −7 to 56, with a greater number being associated with a higher risk of fall or fracture. Fig. 2 shows the probability of a fall or fracture for each point increase in the risk score and the prevalence of these scores in our study population. The predicted probabilities ranged from 2.8% when no predictors were present to 88.8% when all the predictors were present. The AUC of the risk score was 0.70.

The diagnostic and predictive values for each risk score were calculated to determine the most appropriate cut-off point (Table 3). The cut-off with the highest sum of sensitivity and specificity was identified as a total score ≥9, with 68% sensitivity, 60% specificity, PPV 13%, and NPV 96%.

4. Discussion

4.1. Principal findings

This large cohort study conducted over a 5-year period identified major risk factors for falls and fractures in the elderly. It provides two approaches to screening that can be easily applied in a general practice setting without the need for patients to attend functional assessments. Routinely collected GP computer data power these screening tools. They could be easily integrated into existing computerized medical record systems to provide screening tools for the practice population; the decision tree–based version being used as an opportunistic screening tool, and the database-driven risk score being used for systematic targeting of falls prevention services.

Increased age, female sex, and previous falls were the three strongest risk factors for falls in our model. This is consistent with findings from other large cohort studies [7,12,19,20]. Interestingly, the presence of nocturia and urinary incontinence were the next strongest predictors for falls or fractures in our study. The relationship between nocturia and falls has not been previously reported. Possible explanations for this association could be that individuals who are getting up at night to pass urine may be exposing themselves to increased opportunities when a fall could occur and when combined with the urgency of nocturia and the potential decreased visibility at night, this could increase the likelihood of a fall occurring. Additionally, these individuals may be on nightly α-blocker therapy for treatment of their nocturia, which could induce postural hypotension and contribute to falls. Only two previous studies have noted an association with urinary incontinence and falls and both of these called for further research into this area [12,29]. Our study supports these findings and provides further evidence for this relationship. The strong link

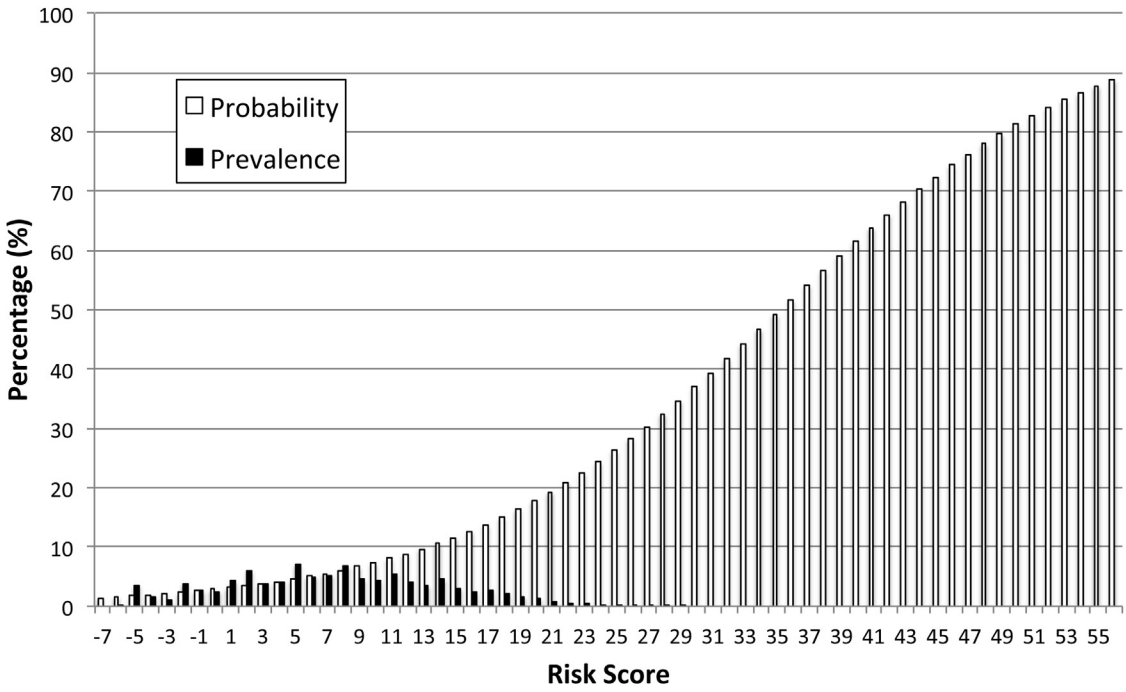

Fig. 2. The probability of a fall of fracture for each point increase in the total risk score (white bars) and the prevalence of each of these scores (black bars).

between sedative medications and anti-depressant use with falls, which has been previously documented in a number of studies, was also confirmed by our results [5,12,14,30]. This suggests these medications should be prescribed with caution in individuals identified as high risk for falls.

In contrast to previous studies, presence of a carer, use of anti-inflammatory medications, and dizziness were not found to be significant predictors of falls in this study. The population in this study is the largest to date used to identify predictors for falls in the elderly, with 135,433 participants, compared with population sizes of no greater than 4,000 in previous studies [17,18,21,35]. This allowed us to assess the importance of a wide range of potential risk factors, including those with a relatively low incidence, in a representative population to produce a strongly validated risk model. Smaller studies conducted over shorter periods of time would have lower number of falls outcomes requiring medical attention, which could explain the differences in variables found to be significant in our study. This study focused on falls requiring medical attention rather than minor falls that may occur in the community and go unreported to GPs. This may be another contributing factor for the variation in risk factors found in this study when compared with other studies that have looked at all falls.

4.2. Implications

The predictors identified from our risk model were assimilated into a decision tree to provide an opportunistic screening tool. This could be a paper-based decision tree or developed into an automated computer prompt that would be used by GPs when assessing elderly patients. It is based on information recorded in routine computerized records from previous and current consultations and therefore accessible at the time of the consultation. Use of computerized prompts is common in general practice and supports chronic disease management, preventive procedures such as immunization or highlights potential prescribing issues [24]. Although we acknowledge that important information can be gathered by more detailed assessments and questionnaires, it is difficult to apply these to all elderly patients without extending the length of GP consultations. The decision tree identified five high-risk end points, with individuals classified into these groups being considered for referral to falls prevention services.

The background probability of a fall in our population was 8%. Using this decision tree, individuals with a falls risk ranging from 10% to 24% were classified as high risk (38.5% of study population). This method of classification accurately identified 53% of individuals who went on to have a future fall, with only 29% of individuals who did not have a fall during our 30-month follow-up period being considered for referral to falls prevention services.

To our knowledge, there are only two existing classification trees for prediction of falls in the elderly, and they are both solely for the prediction of recurrent fallers, defined by at least two falls within a 6-month period [36,37]. Although these are useful tools with high predictive accuracy, this outcome measure will only identify a small percentage of all individuals who have a fall [7,19]. Our classification tree extends this outcome measure to include any future fall, including single episodes, which allows us to identify a

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Table 3. Diagnostic and predictive values of the risk score for falls and fractures at different cut-off points

Cut-off score (≥)	Sensitivity (%)	Specificity (%)	Σ (%)	PV+	PV−
−6	100.0	0	100	8	0
−5	100.0	0.2	100	8	98
−4	99.3	4	103	8	98
−3	98.9	5.7	105	8	98
−2	98.7	6.8	106	8	98
−1	97.7	10.9	109	9	98
0	96.7	13.6	110	9	98
1	95.9	16.3	112	9	98
2	94.5	20.8	115	9	98
3	91.3	27.1	118	10	97
4	89.1	31.1	120	10	97
5	86.7	35.5	122	10	97
6	82.0	42.8	125	11	96
7	78.3	47.9	126	11	96
8	73.8	53.3	127	12	96
9	**67.8**	**60.1**	**128**	**13**	**96**
10	63.0	64.6	128	13	95
11	58.0	68.8	127	14	95
12	51.7	74.2	126	15	95
13	46.1	78.2	124	15	94
14	41.2	81.5	123	16	94
15	34.1	85.9	120	17	94
16	28.9	88.7	118	18	94
17	24.1	91	115	19	93
18	19.4	93.4	113	20	93
19	14.8	95.3	110	21	93
20	11.2	96.8	108	23	93
21	8.2	97.8	106	25	93
22	6.3	98.5	105	26	92
23	5.0	98.9	104	28	92
24	3.6	99.2	103	28	92
25	2.7	99.4	102	30	92
26	1.9	99.6	102	32	92
27	1.2	99.8	101	30	92
28	0.8	99.9	101	32	92
29	0.5	99.9	100	31	92
30	0.2	99.9	100	27	92
31	0.2	100	100	31	92
32	0.1	100	100	33	92
33	0.0	100	100	80	92

Abbreviations: Σ, sum of sensitivity and specificity; PV+, positive predictive value; PV−, negative predictive value.

Numbers in bold represent suggested cut-off score with the highest sum of sensitivity and specificity.

larger proportion of fallers and therefore provides a fall-assessment screening tool with a greater scope for benefit.

The systematic screening tool used a risk score based on multiple variables collected during routine care. It is the first risk score for falls that does not require potentially time-consuming face-to-face mobility assessments. The range of scores varies from −7 to 56 points, with a 2.8% probability of falling when no risk factors are present (score 0), ranging to 88.8% when all factors are present (score 56). The statistical optimum cut-off point was determined by calculating the sum of sensitivities and specificities for each risk score, with the highest value occurring at a cut-off of ≥9. This cut-off would identify 68% of individuals in our population who had a fall. A total of 40% of non-fallers would also be included in the high-risk group. The choice of cut-off point, however, cannot be purely based on statistics. Altman [38] proposes that the optimum cut-off point for screening tools should be decided according to the relative costs (financial and otherwise) of the screening test, which is related to the false positives and false negatives and the costs of the prevention strategy that positive individuals will be referred to undertake. Higher cut-off points produce greater predictive accuracy with fewer total numbers recommended for referral, but this is at the cost of identifying a smaller proportion of individuals who went on to have a fall. As we propose this score to be used as a screening tool to guide referral to falls prevention services, a lower cut-off point with high sensitivity would be recommended to refer as many future fallers as possible. In reality, the cut-off point would be determined by finding a balance between the cost of the interventions and the health-care savings achieved by preventing a fall, taking into account local funding and availability of falls prevention services to determine the number of elderly individuals who can be referred to these services.

The accuracy of our risk model and risk score was assessed using the AUC. Previous studies have reported AUCs ranging between 0.65 and 0.79 (median 0.71) [7,12,20,21]. Our risk model had an AUC of 0.72, which indicates that 72% of individuals can be correctly classified using this risk model making it a good model for prediction of falls, only one study reported a higher AUC [7]. Our risk score had an AUC of 0.70, again comparing well in comparison with previous risk scores, which had AUCs between 0.66 and 0.79 (median 0.70) [19,21,22,39].

An advantage of this risk score is that it is based on standardized Read codes that are used across all UK GP practices; and although the UK's Read codes are due to be phased out, there is a mapping system to the systematized nomenclature of medicine clinical terms (SNOMED CTs). Although SNOMED CT has limitations, it is much more widely used internationally [34,35]. Hence this approach could be easily integrated into GP electronic patient record systems as part of their decision support system, to allow automatic calculation of falls risk as part of a template to save time and flag-up high-risk individuals.

4.3. Limitations

The limitations of this study are that the data used were collected from Read codes recorded during GP consultations and supplemented by information from hospitals and other health-care organizations that forward details to the GP practices for upload to the database. Although this means our model is based on information that GPs have readily available to them and which is routinely collected, our results are reliant on accurate documentation by GPs of the appropriate codes and on the administrative abilities of the practice to upload information to the database. There will inevitably be some cases where information does not

get recorded or uploaded, which may result in the impact of some factors being undervalued. Additionally, not all elderly individuals experiencing a fall or fracture will inform their GP. Patients with falls that present to their GPs are more likely to be those requiring medical attention, rather than minor falls where little or no injuries were sustained. This explains why the number of falls and fractures in our study population is lower than that reported previously, and it is likely to be an underestimate of the true occurrence of all falls and fractures in the population. A recent Cochrane review found that although 30% of people aged over 65 years experience a fall in the community each year, only one in five falls may require medical attention, which is in concordance with the 8% of falls reported in our study [16]. It may also explain why a different cohort of risk factors was found to be significant in this study when compared with previous studies, where occurrence of any fall was used as the outcome measure. Although use of this data set results in missing out a proportion of individuals who have had a fall, it makes the screening tools more selective for individuals with falls requiring medical attention, which are the group who would benefit most from referral to falls prevention services.

4.4. Further research

Further work is needed to validate these screening tools in other elderly populations, before conducting a randomized clinical trial to assess whether implementation in general practice to identify individuals for referral to falls prevention services reduces the occurrence of falls and fractures in this population. Additionally, extending our study to include further variables routinely recorded in GP databases may reveal additional risk factors for falls and increase the predictive accuracy of our risk score further.

It is not known whether systematic or opportunistic approaches to screening are likely to be more effective in this context and further research is needed to assess what tools or combination of tools are required in primary care. We have already alluded to how in atrial fibrillation, opportunistic screening is probably the more effective approach [25], whereas for mammography and several other preventive programmes implemented in primary care, a systematic approach appears to be more effective [40]. In some cases, such as chlamydia, neither approach appears to be satisfactory [41], although it has been accepted for some decades that both systematic and opportunistic screening have a place in the recording of blood pressure and detection of hypertension in primary care [42].

5. Conclusion

This study shows that falls can be predicted in an elderly population using information that is readily available on GP databases. The decision tree and risk score are easy to apply, non−time consuming and differ from others by not requiring additional mobility assessments. Additionally, the risk score can be integrated into existing GP databases to provide an automated screening tool for falls. Once validated, they can be used in routine GP falls assessments to identify individuals for interventions to prevent falls.

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