Risk factors and risk assessment tools for falls in hospital in-patients: a systematic review

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Abstract

Objective: to identify all published papers on risk factors and risk assessment tools for falls in hospital inpatients. To identify clinical risk assessment tools or individual clinical risk factors predictive of falls, with the ultimate aim of informing the design of effective fall prevention strategies.

Design: systematic literature review (Cochrane methodology). Independent assessment of quality against agreed criteria. Calculation of odds ratios and 95% confidence intervals for risk factors and of sensitivity, specificity, negative and positive predictive value for risk assessment tools (with odds ratios and confidence intervals), where published data sufficient.

Results: 28 papers on risk factors were identified, with 15 excluded from further analysis. Despite the identification of 47 papers purporting to describe falls risk assessment tools, only six papers were identified where risk assessment tools had been subjected to prospective validation, and only two where validation had been performed in two or more patient cohorts.

Conclusions: a small number of significant falls risk factors emerged consistently, despite the heterogeneity of settings namely gait instability, agitated confusion, urinary incontinence/frequency, falls history and prescription of ‘culprit’ drugs (especially sedative/hypnotics). Simple risk assessment tools constructed of similar variables have been shown to predict falls with sensitivity and specificity in excess of 70%, although validation in a variety of settings and in routine clinical use is lacking. Effective falls interventions in this population may require the use of better-validated risk assessment tools, or alternatively, attention to common reversible falls risk factors in all patients.

Keywords: hospital, accidental falls, prevention, prediction, risk factors

Introduction

Falls are common among hospital inpatients. Rates from 2.9–13 falls per 1,000 bed days have been reported [1]. Up to 30% of such falls [2] may result in injury, including fracture, head and soft tissue trauma, all of which may in turn lead to impaired rehabilitation and co-morbidity [3]. Falls are also associated [4, 5] with higher anxiety and depression scores, loss of confidence and post-fall syndrome. Not only are they costly for individual patients and for hospitals, but they may result [6, 7] in anxiety or guilt among staff, complaints or litigation from patients’ families. There may be a feeling that something should have been done to prevent the fall and that someone is accountable.

We know that many hospital patients recovering from acute illness may go through a period of transient risk and that others, with chronic gait instability and cognitive impairment, may be at risk of falling throughout admission [8]. Moreover, effective rehabilitation entails an inevitable risk of falls as patients are encouraged to regain independent mobility. It seems intuitively likely however, that some falls are both predictable and preventable.

Systematic review of the literature on falls prevention in hospitals has found no consistent evidence for single or multiple interventions to prevent falls [9]. More definitive work in this field has been recognised as a key falls research priority [10]. There is better evidence for falls prevention in older people dwelling in the community [10, 11]. However, such individuals are likely to have different characteristics.
from patients admitted to hospital. Whilst we know that falls are the result of multiple synergistic pathologies and risk factors [12], we do not know to what extent the nature and prevalence of these risk factors is different among hospital inpatients, and therefore whether successful interventions can be extrapolated from the community. Moreover, as patients may only be in hospital for a short time, long-term interventions (e.g. exercise programmes) are unlikely to be effective. It does seem likely, however, that any successful intervention to prevent falls in hospital inpatients might rest both on a knowledge of the reversible risk factors for falls in this group and on an ability to predict high risk of falling in individual patients.

With regard to risk prediction, there are a number of clinical risk assessment tools in the literature whose derivation, weighting, validation and usefulness are obscure. Wyatt and Altman [13] laid down ‘gold standard’ criteria for the use of such tools. Essentially, they should be validated prospectively, using sensitivity/specificity analyses, in more than one population, with good face validity, inter-rater reliability and adherence from staff and transparent, simple calculation of the score.

A better knowledge of the nature and prevalence of risk factors for falls in hospital inpatients and of our ability to identify high-risk patients is an important step in the design of future falls prevention interventions in this group. They may also be applicable to other facilities, which provide care for post acute patients, such as Intermediate Care units in the UK or skilled nursing facilities in the US.

Risk factors

Only papers relating to falls in hospital inpatients were included. Using Wyatt and Altman’s Criteria [13] as a template, risk assessment tools must have been subjected to prospective validation (not simply retrospective fitting to an initial dataset) with sufficient data to allow the calculation of sensitivity, specificity, negative and positive predictive value, together with OR and CI. It was considered methodologically preferable that tools (vide supra) should have been validated in more than one setting, but those validated only once are included in final analysis.

Statistical analysis [18, 19]

All published papers with the potential for inclusion were scrutinised to determine which of the following quantities were explicit or could be deduced from information given in the original text: prevalence of fallers in the sample studied, prevalence of risk factor in the sample, estimated sensitivity, estimated specificity, estimated positive predictive value, estimated negative predictive value, estimated OR, estimated risk ratio. The authors were also interested in whether CI were provided for any or all of these estimates. Finally, a significance probability (P value) for a hypothesis of zero association between falling status and the presence of a risk factor was sometimes stated. In each case, where full datasets were published, the authors checked the values and CI provided, with occasional amendments to those in the published data.

Typically only some of the necessary data enabling post hoc calculations of this kind were published and the authors noticed incidentally a strong trend with the passage of time to reduce the amount of numerical information provided to the reader.

Estimates for these quantities require to be estimated from experiment. Data are collected as follows, and in a full statement of experimental outcome, all four numbers a, b, c and d would be provided in an account of a study involving n = a + b + c + d subjects (Table 1).

The prevalence of fallers may be estimated by

\[ \text{preva} = \frac{(a + c)}{(a + b + c + d)} \]

not to be confused with the estimated prevalence of the risk factor (i.e. the proportion of those in the risk category) given by the fraction

\[ \frac{(a + b)}{(a + b + c + d)} \]

The estimated sensitivity and specificity are

\[ \text{sens} = \frac{a}{(a + c)} \]
\[ \text{spec} = \frac{d}{(b + d)} \]

The corresponding estimates for the two predictive values are

\[ \text{ppv} = \frac{a + b}{(a + b + c + d)} \]
\[ \text{ppn} = \frac{d}{(c + d)} \]

Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Faller</th>
<th>Non-faller</th>
</tr>
</thead>
<tbody>
<tr>
<td>In risk category</td>
<td>a+b+c+d</td>
<td>a+b+c+d</td>
</tr>
<tr>
<td>Not in risk category</td>
<td>a+b+c+d</td>
<td>b+d+c+d</td>
</tr>
</tbody>
</table>
Table 2.

<table>
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<tr>
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<th>Fallers</th>
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<th>Total</th>
</tr>
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<tbody>
<tr>
<td>Drug</td>
<td>209</td>
<td>169</td>
<td>378</td>
</tr>
<tr>
<td>No drug</td>
<td>68</td>
<td>108</td>
<td>176</td>
</tr>
<tr>
<td>Total</td>
<td>277</td>
<td>277</td>
<td>554</td>
</tr>
</tbody>
</table>

The estimated odds ratio is
\[ \text{OR} = \frac{ad}{bc} \]
and the estimated risk ratio is given by
\[ \text{RR} = \frac{(a \times (c + d))/(c \times (a + b))}{(1 - \text{prev})} \]

CI may be stated for all quantities estimated using either exact binomial methods (sensitivity, specificity, positive predictive value and negative predictive value) or Breslow-Day (OR). A P-value can be provided for the hypothesis of no association between risk category and falling status using an exact contingency test such as Fisher’s exact test.

Taking Ballinger and Ramsay [20] as an example, we are told that of 277 fallers, 209 had received a psychotropic drug on the day of the accident; of 277 accident-free matched controls, 169 had received a psychotropic drug on the day of the accident. From the resulting table the following estimates are provided (sensitivity, specificity, positive and negative predictive value).

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<td>554</td>
</tr>
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estimated sensitivity = 209/277 = 0.755 (0.699, 0.804)
estimated specificity = 108/277 = 0.390 (0.332, 0.450)
estimated positive predictive value = 209/378 = 0.553 (0.501, 0.604)
estimated negative predictive value = 108/176 = 0.614 (0.537, 0.686)
estimated odds ratio = (209×108)/(68×169) = 1.96 (1.35, 2.85)

and, finally, the significance probability (P-value) for a hypothesis of zero association between drug use and falling status is \( P = 0.000358 \).

Notice in this case (and as is made clear in the paper) the experiment was designed to incorporate the same number of fallers as non-fallers: in the jargon, the sample was a stratified random sample, not a simple random sample. So the estimated prevalence of fallers 277/554 = 1/2 provides no information about the proportion of fallers in the population.

Later papers offer much less detail. Typically two or three estimates are provided (sensitivity, specificity, OR) with or without confidence intervals. Usually fall prevalence may be deduced from the description of the study design. If the total sample size \( n \) is given then some of the frequencies \( a, b, c, d \) may be deduced. Finally, there is considerable redundancy amongst the listed quantities: for instance, if sensitivity and specificity are both given (or if positive and negative predictive values are both given) then the OR may be deduced directly:
\[ \text{OR} = \frac{a 	imes (c + d)}{b 	imes (a + b)} \]
\[ \text{RR} = \frac{(a \times (c + d))/(c \times (a + b))}{(1 - \text{prev})} \]

Other relationships include
\[ \text{ppv} = \frac{(a 	imes (c + d))}{(a 	imes (c + d)) + (1 - \text{spec}) \times (1 - \text{prev})} \]
\[ \text{npv} = \frac{(b 	imes (1 - \text{prev}) + (1 - \text{prev}) \times (1 - \text{spec}) \times (1 - \text{prev}))}{(1 - \text{prev}) \times (1 - \text{spec}) \times (1 - \text{prev})} \]
\[ \text{rr} = \frac{\text{ppv}}{(1 - \text{npv})} \]

By inferences of this kind (and occasionally because the complete data were provided in the published paper) the results in Table 3 were obtained.

Results

Risk factors

28 papers were identified in total. A total of 13 papers were identified which met the criteria for inclusion [3, 20–32]. The risk factors and ORs are summarised in Table 3. Five papers contained extensive data but insufficient to allow the calculation of OR and CI and were therefore excluded [33–39]. A further 10 papers [40–51] contained minimal or purely observational data and were also excluded.

Risk assessment tools (Table 4)

Forty-seven papers with mention of falls risk assessment tools were identified. However, only two risk assessment tools (Morse 1989 [1], Oliver 1997 [28]) fulfilled the criteria of prospective validation with sensitivity/specificity analysis in development and then remote cohorts [52, 53]. Kuipers 1993 [54] performed a validation of the Innes [55] Score (itself never validated). Schmid [31] described prospective validation in one cohort. Nyberg [56] described a prospective validation of the Downton Index in stroke patients.

A number of other descriptions of sensitivity/specificity analysis applied only to retrospective fitting of data to an original dataset on risk factors and were therefore excluded [3, 22, 24, 34]. Thirty-nine further papers purporting to describe falls risk assessment tools were identified [57–97]. Other papers were excluded because they contained no validation study and/or insufficient data to allow the calculation of sensitivity, specificity, negative and positive predictive value.

Discussion

Thirteen studies were identified which described risk factors (factors significantly more prevalent in fallers than non-fallers), in a variety of inpatient settings. Despite the heterogeneity of the settings, populations and risk factors studied, a small number of factors repeatedly emerged as significant: gait instability; lower limb weakness; urinary incontinence/frequency or need for assisted toileting; previous fall history; agitation/confusion or impaired judgement; prescription of ‘culprit’ drugs, in particular centrally acting sedative hypnotics. The prevalence of these risk factors is significantly higher than one would expect to see in community dwelling older persons [12], perhaps confirming the impression that different intervention strategies may be necessary in this group. A very large number of papers were identified in which falls risk assessment tools were described, but only five had ever been subjected to validation in one, let alone two, patient populations and most had obscure derivation and arbitrary scoring, giving no basis for use in clinical practice despite their publication in peer-reviewed journals. Those tools for which the validation methodology was sound did show high sensitivity and specificity in predicting falls under research conditions, but had not been validated in multiple settings or used as part of effective falls prevention strategies.
<table>
<thead>
<tr>
<th>Study, setting, design</th>
<th>Risk factors</th>
<th>Fallers*</th>
<th>RF**</th>
<th>SENS</th>
<th>CI for SENS</th>
<th>SPEC</th>
<th>CI for SPEC</th>
<th>OR</th>
<th>CI for OR</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ballinger 1976</strong>&lt;br&gt;UK Psychiatric ward Case control (n = 277 each group). Retrospective matching. Univariate analysis.</td>
<td>Psychotropic drugs on day of accident</td>
<td>0.5</td>
<td>0.68</td>
<td>0.751</td>
<td>0.696–0.801</td>
<td>0.390</td>
<td>0.332–0.450</td>
<td>1.93</td>
<td>1.33–2.67</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Bates 1995</strong>&lt;br&gt;Urban tertiary care hospital, USA. Retrospective matched case-control (n = 62 each group). 40 variables. Multivariate regression.</td>
<td>Score on Confusion and Mobility (CaM) assessment before fall &gt;1</td>
<td>0.5</td>
<td>0.306</td>
<td>0.484</td>
<td>0.355–0.614</td>
<td>0.871</td>
<td>0.761–0.943</td>
<td>6.33</td>
<td>2.54–15.6</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Byers 1990</strong>&lt;br&gt;Acute stroke ward USA. Case control matched by admission date. (202 fallers, 111 non-fallers). Multivariate regression.</td>
<td>Impaired decision making</td>
<td>0.645</td>
<td>0.0415</td>
<td>0.064</td>
<td>0.0346–0.108</td>
<td>1</td>
<td>0.967–1</td>
<td>Inf</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td><strong>Chu 1999</strong>&lt;br&gt;Acute hospital. Hong Kong. Case-control (n = 51 each group), assessed for 29 clinical and 22 functional risk factors. Multivariate regression.</td>
<td>Lower limbs weakness</td>
<td>0.5</td>
<td>0.235</td>
<td>0.392</td>
<td>0.258–0.539</td>
<td>0.922</td>
<td>0.811–0.978</td>
<td>7.58</td>
<td>2.19–25.8</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Gales 1995</strong>&lt;br&gt;Acute care hospital. Matched Case control (n = 100 each group). Prevalence of common disease states and drugs. Univariate analysis.</td>
<td>Congestive heart failure</td>
<td>0.5</td>
<td>0.285</td>
<td>0.37</td>
<td>0.276–0.472</td>
<td>0.8</td>
<td>0.708–0.873</td>
<td>2.35</td>
<td>1.22–4.64</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Gluck 1996</strong>&lt;br&gt;Acute geriatric wards UK. Matched case control (n = 50 each group). 25 risk factors studied.</td>
<td>Present confusion/disorientation</td>
<td>0.5</td>
<td>0.60</td>
<td>0.8</td>
<td>0.663–0.9</td>
<td>0.6</td>
<td>0.452–0.736</td>
<td>6</td>
<td>2.32–15.5</td>
<td>0.03</td>
</tr>
<tr>
<td><strong>Janken 1986</strong>&lt;br&gt;Tertiary care hospital. Retrospective chart audit. 331 fallers vs 300 non-fallers. Multivariate regression.</td>
<td>Confusion</td>
<td>0.525</td>
<td>0.214</td>
<td>0.287</td>
<td>0.239–0.339</td>
<td>0.867</td>
<td>0.823–0.93</td>
<td>2.62</td>
<td>1.73–3.98</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Lichtenstein 1994</strong>&lt;br&gt;Canada. Acute care hospitals. Case control (129 falls, 234 controls) for falls resulting in hip fracture. Multivariate regression.</td>
<td>Prior in hospital falls + confusion</td>
<td>0.355</td>
<td>0.223</td>
<td>0.341</td>
<td>0.26–0.43</td>
<td>0.842</td>
<td>0.789–0.886</td>
<td>2.76</td>
<td>1.62–4.59</td>
<td>0.00</td>
</tr>
</tbody>
</table>

* Denotes significant predictor at p < 0.05. ** In the analysis, we used a random effects model. The ORs are calculated with 95% confidence intervals (CI).
Moreover, the presence of a small number of consistent risk factors seemed to predict most falls.

The literature review and assessments of methodological quality were carried out with explicit and recommended methods and it is unlikely that many important studies were overlooked, nor methodologically sound studies unfairly rejected. However, there are limitations in the nature of the original studies identified. First, only risk factors chosen for initial study by the researchers could be evaluated. For instance, there is little mention of environmental risk factors for falls and moreover, there is little mention of environmental risk factors for falls and only a handful of studies where detailed clinical assessment of patients was carried out. Secondly, the heterogeneity of settings mean that risk assessment tools may not be so effective when employed in settings or patient populations different from those used in the index study. This suspicion seems to be confirmed by the fact that the STRATIFY score (Table 4) was

<table>
<thead>
<tr>
<th>Table 3. continued</th>
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</thead>
<tbody>
<tr>
<td>Study, setting, design</td>
</tr>
<tr>
<td>Morse 1987</td>
</tr>
<tr>
<td>Canada, acute care hospital. Matched case control (n = 100 each group). 34 risk factors studied (intrinsic and environmental). Multivariate analysis</td>
</tr>
<tr>
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</tr>
<tr>
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</tr>
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</tbody>
</table>

1Fallers = proportion of subjects in this sample who were categorised as fallers.
2RF = proportion of subjects in this sample who possessed the risk factor. In a random sample both these proportions would offer useful estimates of the proportion in the population who are fallers, and who are at risk, respectively. In most of these studies, however, the subjects were not randomly selected: they were designed to have as many fallers as non-fallers (e.g. Ballinger, Bates, Chu, Salgado, Schmid ...). So this ‘estimate’ is not an estimate at all, just confirmation that the experimental design was stratified as intended. Similarly, the usefulness of RF as an estimate is reduced where the method for sampling subjects is stratified.
Table 4. Prospective validation studies of falls risk assessment tools

<table>
<thead>
<tr>
<th>Study &amp; Setting</th>
<th>Design</th>
<th>Sensitivity % (CI)</th>
<th>Specificity % (CI)</th>
<th>PPV % (CI)</th>
<th>NPV % (CI)</th>
<th>Odds ratio (CI)</th>
<th>P*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kuipers^52 1993. 10 Medical Units, 276 beds, Holland.</td>
<td>Prospective Validation of Innes Score^3, 2968 patients (86 falls)</td>
<td>89.3 (78.1, 96.0)</td>
<td>73.5 (71.7, 75.2)</td>
<td>7.3 (5.4, 9.5)</td>
<td>99.7 (99.3, 99.9)</td>
<td>23 (10.1, 55.5)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Morse^1 1989 Canada. 16 units of varying types, long term, acute and rehabilitation. Only 41% patients over 65 years.</td>
<td>Prospective Validation of Morse Score ≥45 as cut-off for high risk. 2689 patients (147 falls).</td>
<td>73.2 (57.1, 85.8)</td>
<td>75.1 (73.4, 76.7)</td>
<td>4.3 (3.0, 6.1)</td>
<td>99.4 (99.0, 99.7)</td>
<td>8.2 (4, 16.7)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>McCollam^50 1995. US Veterans Administration Hospital 40 bed cardiology general medical unit.</td>
<td>Prospective Validation of Morse Score on 483 patients (23 fallers), using Morse Score ≥45 as cut-off.</td>
<td>95.7 (78.1, 99.9)</td>
<td>54.0 (49.2, 58.8)</td>
<td>9.9 (6.3, 14.6)</td>
<td>99.6 (97.7, 100)</td>
<td>25.9 (4.2, 528.4)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Oliver^28 1997 Phase 2. UK teaching hospital acute geriatric unit. 78 beds.</td>
<td>Prospective validation of STRATIFY Score≥ 2 on 395 patients, (71 falls) using score of ≥2 as cut-off.</td>
<td>93.0 (84.3, 97.7)</td>
<td>87.7 (83.6, 91.0)</td>
<td>62.3 (52.3, 71.5)</td>
<td>98.3 (96.0, 99.4)</td>
<td>93.7 (35.2, 253.3)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Oliver^28 1997 Phase 3. UK district general hospital, acute and rehabilitation wards for patients over 75 years.</td>
<td>Prospective Validation of STRATIFY Score on 446 (79 falls) using Score of ≥3 as cut-off.</td>
<td>54.4 (42.8, 65.7)</td>
<td>87.6 (83.8, 90.8)</td>
<td>48.9 (38.1, 59.8)</td>
<td>89.8 (86.2, 92.8)</td>
<td>8.4 (4.8, 14.6)</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Coker^42 2003 Canadian Geriatric Rehabilitation Unit.</td>
<td>Prospective validation of STRATIFY score on 432 patients (111 falls) using ≥2 as cut-off.</td>
<td>73.7 (56.9, 86.6)</td>
<td>45.2 (40.2, 50.2)</td>
<td>11.5 (7.8, 16.2)</td>
<td>94.7 (90.4, 97.4)</td>
<td>1.07 (2.31, 5.30)</td>
<td>0.026</td>
</tr>
<tr>
<td>Nyberg^44 1996. Swedish Geriatric Stroke rehabilitation unit.</td>
<td>Prospective validation of Downton Score≥ 2 on 135 patients (142 falls) Score ≥3 used as cut-off.</td>
<td>90.6 (79.3, 96.9)</td>
<td>26.8 (17.6, 37.8)</td>
<td>44.4 (34.9, 54.3)</td>
<td>81.5 (61.9, 93.7)</td>
<td>3.5 (1.2, 10.3)</td>
<td>0.015</td>
</tr>
<tr>
<td>Schmid^11 1990. US Veterans administration hospital.</td>
<td>Prospective validation of Schmid Score≥ on 2405 patients (54 fallers). Score ≥3 used as cut-off</td>
<td>92.5 (79.6, 98.4)</td>
<td>78.2 (73.1, 82.8)</td>
<td>36.6 (27.3, 46.8)</td>
<td>98.7 (96.3, 99.7)</td>
<td>44.3 (13.2, 172.4)</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

*Sensitivity = true positive rate, or what percentage of falls occurred in patients identified as ‘high risk’.

Specificity = true negative rate, or what percentage of non-falls occurred in patients identified as ‘low risk’.

PPV (Positive Predictive Value) = what percentage of patients identified as ‘high risk’ went on to fall.

NPV (Negative Predictive Value) = what percentage of patients identified as ‘low risk’ did not go on to fall?

P value for hypothesis that there is no association between risk status and falling status.

Ratio of odds of falling in high risk patients v odds of falling in low risk patients. The more the OR exceeds 1, the greater the suggestion that high-risk status increases the likelihood of falling.

The Innes score is not described in Table 3 as it was not derived from an initial case control or cohort study but simply from literature review. The elements are: previous trauma; disorientation; impaired judgement; sensory disorientation; muscle weakness; multiple diagnoses; language barrier.

The Morse Score is partially described in Table 3, comprising six risk factors identified from case control study. These elements were weighted to give an overall total possible score of 125. 45 was chosen by the authors as the best cut-off for analysis, though data are available in the validation cohorts for all scores.

The Stratify score is partially described in Table 3, as the five risk factors identified from case-control study. These were used (unweighted) to form a five-point risk score. As with the Morse score, data are described for all scores in all three validation cohorts, but the authors picked the most operationally useful cut-off in each cohort for further analysis.

The Downton score is not described in Table 3 as it was derived from literature review, rather than case control or cohort study. The elements are: previous fall history; medication; sensory deficit; confusion; gait; with a total score of ≥3 indicating high risk.

The Schmid score is partially described in Table 3, as the five risk factors derived from initial case-control study. Total possible score is 6 and ≥3 was used as the definition of ‘high risk’.

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progressively less effective in settings remote from the original validation cohort. (Though one might argue that the remarkable conservation of significant risk factors across various inpatient settings suggests that the phenomena are fairly universal). Thirdly, those studies where retrospective fitting of risk assessment was applied to original data did suggest useful predictive power, but this was not confirmed by subsequent prospective validation. Fourthly, those risk factors which predict falls effectively are not necessarily those which cause them.

The relationship between predictive association and causation of falls requires empirical investigation with attempts to prevent falls. There is no consistent evidence of effective interventions to prevent falls among hospital inpatients [9, 10], although many of the published fall prevention studies were underpowered or methodologically flawed. It seems likely, however, that a strategy based on the identification and (where possible) reversal of common falls risk factors is most likely to succeed. The data here give us a clear indication of the likely target areas for intervention, though within the short time that most patients are in hospital, certain interventions (e.g. medication review) may be more feasible than others (e.g. gait instability). There are few data on extrinsic factors (e.g. staffing levels and environmental safety) which might also be amenable to modification.

An allied approach is to use well-validated, simple and adhered-to risk assessment tools to target individual patients at high risk of falling. However, the feasibility and usefulness of using such tools should probably be piloted in a locality before incorporation in falls prevention programmes. Wide validation work has not been performed for any of the tools on the scale that exists, for instance, for the Glasgow Coma Scale [97], Apache Score [98] or Waterlow Index [99], used for prognostication and risk assessment in other areas of clinical practice. A further limitation is in the operational properties of the risk assessment tools. For instance, a tool with high negative predictive value or specificity might provide accurate reassurance to staff that patients are at low risk of falling, but might have low positive predictive value or sensitivity, meaning that interventions are too widely targeted. Even the best, validated tools will fail to predict a significant number of falls. However, it is both intuitive and evidence-based [100] that patients who have already fallen are at high risk of further falls and that assessment is worthwhile, whereas for those who fall only once during admission (about 50%), attention to reversible risk factors or risk status from the time of admission may be worthwhile.

Perhaps the best way forward is to accept that as none of the validated tools can be recommended for wholesale implementation, clinicians should move away from the notion of categorising people as low or high risk. Energies may be more productively directed towards identifying common modifiable risk factors in all patients and ensuring that people who do fall in hospital receive a proper post-fall assessment. Regard any patients who have already fallen on the ward as ‘high risk’ for future falls (shown to have used a validated risk assessment early during admission to help in the prediction of first fall), target common reversible falls risk factors in all patients—whatever supposed falls risk status—and attend to common environmental safety measures. It must be re-iterated that the effectiveness approach has not been consistently evaluated in the prevention of falls among hospital inpatients and that caution is required before widespread, wholesale introduction of assessments and interventions, which are potentially cost and labour intensive and based on insubstantial evidence.

### Key points
- Accurate assessment of risk is important in designing interventions to prevent falls in inpatients.
- A small number of readily identifiable and potentially reversible risk factors for inpatient falls has been repeatedly identified in studies.
- Risk assessment tools with useful operational characteristics and widespread validation are few.
- Even the best will fail to classify a high percentage of fallers.
- Perhaps the key is to look for reversible fall risk factors in all patients.

### References
Risk factors and risk assessment tools for falls in hospital in-patients


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