BMJ Open

Clinical prediction models for hospital falls: a scoping review protocol

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To cite: Parsons R, Cramb SM, McPhail SM. Clinical prediction models for hospital falls: a scoping review protocol. *BMJ Open* 2021;**11**:e051047. doi:10.1136/bmjopen-2021-051047

► Prepublication history and additional supplemental material for this paper are available online. To view these files, please visit the journal online (http://dx.doi.org/10.1136/bmjopen-2021-051047).

Received 10 March 2021
Accepted 23 August 2021

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ABSTRACT

Introduction Falls remain one of the most prevalent adverse events in hospitals and are associated with substantial negative health impacts and costs. Approaches to assess patients' fall risk have been implemented in hospitals internationally, ranging from brief screening questions to multifactorial risk assessments and complex prediction models, despite a lack of clear evidence of effect in reducing falls in acute hospital environments. The increasing digitisation of hospital systems provides new opportunities to understand and predict falls using routinely recorded data, with potential to integrate fall prediction models into real-time or near-real-time computerised decision support for clinical teams seeking to mitigate fall risk. However, the use of non-traditional approaches to fall risk prediction, including machine learning using integrated electronic medical records, has not yet been reviewed relative to more traditional fall prediction models. This scoping review will summarise methodologies used to develop existing hospital fall prediction models, including reporting quality assessment.

Methods and analysis This scoping review will follow the Arksey and O'Malley framework and its recent advances, and will be reported using Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews recommendations. Four electronic databases (CINAHL via EBSCOhost, PubMed, IEEE Xplore and Embase) will be initially searched for studies up to 12 November 2020, and searches may be updated prior to final reporting. Additional studies will be identified by reference list review and citation analysis of included studies. No restriction will be placed on the date or language of identified studies. Screening of search results and extraction of data will be performed by two independent reviewers. Reporting quality will be assessed by the adherence to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis.

Ethics and dissemination Ethical approval is not required for this study. Findings will be disseminated through peer-reviewed publication and scientific conferences.

Strengths and limitations of this study

- The proposed review will be the first scoping review of hospital fall prediction model development processes.
- This protocol includes a systematic search and adheres to a rigorous, established research framework for study selection and reporting.
- The review will not include a meta-analysis of prediction performance.
- The review will not include studies relating to falls occurring out of the hospital setting.

INTRODUCTION

Falls are one of the most reported adverse events in hospitals internationally and are associated with significant disease burden and costs.[1] A 2015 audit of inpatient falls in the UK reported 6.63 falls per 1000 occupied bed days in acute care hospitals,[2] up from 4.8 in 2005–2006,[3] despite concerted efforts and substantial investment in patient safety measures. Falls have been reported to be associated with additional length of stay and operational costs internationally, including in the USA,[4] Canada[5] and Australia.[6 7]

Multifactorial assessments and associated interventions may reduce falls, suggesting that at least some proportion of hospital falls are preventable.[1 8 9] However, evidence for these approaches may be setting-dependent, with clinical trial evidence supporting only fall prevention approaches that incorporate fall risk assessment in subacute care hospital rehabilitation settings for older adults[10] but not in conventional acute care hospital ward settings.[11] This has caused some to question the value of current approaches to assessing fall risk and targeting fall prevention interventions in acute care hospital settings.[12] A recent non-inferiority trial across 10 hospitals indicated falls did not increase when staff ceased completing multifactorial fall risk assessments and instead used their own clinical reasoning to select interventions from a clinical decision support intervention list without completing the multifactorial fall risk assessment.[13] In addition to demonstrating non-inferiority, after adjusting for historical fall rates at the participating hospitals, the hospital fall incident rate ratio favoured the group that ceased fall risk assessment ratings.[13]

The inability of conventional approaches to identifying patients at risk of falling, including fall risk screening questions and fall risk assessment tools, to successfully guide interventions to reduce fall injuries in acute care hospital settings may be due, at least in part, to poor fall prediction performance. Patient attributes that have been reported to influence fall risk include mental status,[14] toileting needs,[15] mobility impairment,[16] history of falls,[17] medications,[18] diabetes and poor blood glucose control,[19] and age,[20] among many others.[21] However, systematic reviews of conventional approaches to predict fall risk in hospitals report that their performance may not be considered clinically useful.[22] In response to this, the current guidelines from the National Institute for Health and Care Excellence (NICE) advise a pragmatic and simplistic approach to categorising patients as high fall risk if they are either (1) aged 65 years or older or (2) aged 50–64 years and judged by a clinician to be at higher risk of falling because of an underlying condition.[23] Since the NICE guidelines classify most patients in hospital wards as being at high risk of a fall event which occurs for approximately 3.6% of patients,[6] this approach may be sensitive but lacks specificity for guiding specific fall prevention interventions.

The increasing digitisation of hospital information systems in recent years, including the wider adoption of integrated electronic medical records (ieMRs), has laid a foundation for the development and adoption of more advanced approaches to fall risk prediction in hospitals. The use of additional predictors, obtained from ieMR and other digital hospital systems, has been shown to improve risk prediction performance in related clinical contexts.[24] In addition, the potential to integrate high-performing prediction models nested within these systems may enable continuous risk predictions and computerised clinical decision support that is potentially desirable to clinicians[25] and medical associations.[26] The wide array of fields routinely and automatically recorded in ieMRs and associated systems provides an opportunity for the application of a range of advanced statistical modelling and algorithmic approaches that have potential utility in hospital settings.[27] However, studies reporting newer approaches to fall risk prediction, including machine learning and its potential role in computerised clinical decision support systems intended to reduce fall risk, have not yet been systematically collated and considered alongside more conventional methods for predicting hospital falls. The quality of reporting for inpatient fall prediction models has also not been described previously. It is also unknown whether the publication of the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement[28] has led to improved reporting quality in the context of inpatient fall prediction models.

Study rationale

Although a range of approaches to assessing fall risk in hospitals have been available for decades,[29] performance is inconsistent,[30] and validation studies suggest that generalisability of some approaches to fall risk prediction may be poor.[31] Increasing completion rates of conventional approaches to multifactorial fall risk assessment and implementation of associated interventions do not have clinical trial evidence of effect in acute care hospital wards.[32] Poor performance of conventional and non-conventional approaches to fall risk prediction in hospital environments may be influenced by the methods used to develop these fall risk prediction approaches. This scoping review will allow us to summarise methods and sources of data which have already been used in the development of published approaches to in-hospital fall risk prediction, and potentially identify underexplored methods and data sources. It is anticipated that these findings will provide insight into promising approaches for improving fall risk prediction models that have potential to be adopted in computerised decision support solutions suitable for hospital settings, including ieMR environments. Therefore, this review will aim to describe existing approaches to hospital fall prediction model development and the quality of reporting in these studies.

Study objectives

To address this aim, the following objectives have been set: (1) describe sources and predictor variables used for model development in the context of in-hospital fall prediction, (2) describe the development process and algorithmic approaches used, and (3) describe how existing in-hospital fall prediction model reporting adheres to the TRIPOD guidelines.[28]

METHODS

This scoping review will be reported to the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.[33] It will be guided by the Arksey and O'Malley framework[34] as well as recent advances.[35] The framework includes the following five steps:

1. Identifying the research question.
2. Identifying relevant studies.
3. Selecting studies.
4. Charting the data.
5. Collating, summarising and reporting the results.

This review design may identify areas where a systematic review or a meta-analysis is desired to answer a more precise and quantitative research question, but no meta-analysis is planned for inclusion in this scoping review.

Stage 1: identifying the research question

The purpose of a scoping review is to map the literature within a given field, in this case, hospital fall prediction models. Therefore, we will use an iterative process as our understanding of the literature improves, and the questions may be reframed appropriately.

Our review will focus on the following research questions:

1. What clinical prediction models are available for hospital falls?
2. What methods are used to create these models?
3. What predictor variables are used in these models?
4. How well have existing models been reported?

Stage 2: identifying relevant studies

Studies that match the search terms provided will be extracted from CINAHL via EBSCOhost, PubMed, IEEE Xplore and Embase, and will include studies available from database inception to 12 November 2020. This search may be updated prior to submission of the manuscript reporting the findings from this scoping review to ensure the most recent literature is included in the review at time of publication. There will not be any limitations on the document type. The search terms we will use for each database were selected with the consultation of a librarian and can be found in the online supplemental appendix 1.

Eligibility criteria

To enable the exploration of processes and data used to develop approaches for fall risk prediction among hospital inpatients, this review will include studies that developed fall risk prediction approaches and reported a measure of predictive model performance in their development study. Studies that did not report a comparable measure of predictive performance for in-hospital fall prediction will be excluded. Similarly, studies that validated existing models in new samples, focused on use of sensors, accelerometers or other equipment not likely to be widely available in hospitals, or predicted falls that occur within a clinically irrelevant period will be excluded. For the purpose of this review, we consider a clinically irrelevant period to be one that included falls that occurred after hospitalisation, or within the hospitalisation period but with insufficient time to realistically enable a clinical team to be notified of the fall risk and implement risk mitigating actions (eg, studies predicting falls that occur within one minute).

Stage 3: study selection

Search results from each database will be imported into EndNote X9 and duplicates will be removed before being imported into Rayyan.[36] Article titles and abstracts will be assessed against the eligibility criteria by two reviewers. Conflicts will be resolved by discussion or by an additional reviewer.

The same researchers will review the full texts of the included studies against the same eligibility criteria. After full-text review, the reference lists of included studies will be examined for additional studies of relevance.

Stage 4: charting the data

Two reviewers will extract data from 20% of included studies, independently, and discrepancies will be discussed. One of the reviewers will then complete data extraction for all remaining studies. The fields for data extraction adapted from the Joanna Briggs Institute template[37] will include those described in the online supplemental appendix 1. Data fields to be extracted were chosen based on the TRIPOD statement[28] and include identifying details of the study, its design, sample characteristics (including sample size and patient age), data sources, type of fall outcome being predicted, modelling approach and performance.

Stage 5: collating, summarising and reporting the results

A narrative report will summarise the studies with regard to the research questions. Tables will be used to present detailed descriptions of each included study with regard to (1) study design and data sources; (2) model development process, features used and validation method(s); and (3) adherence to TRIPOD reporting guidelines.[28] Aggregated results will also be presented in tables to provide the end user with a summarised view of approaches and strategies used. These results will be interpreted with regard to the research aims and objectives. Gaps in the literature will be identified concerning current standards of reporting and development methods for inpatient fall prediction models.

Patient and public involvement

No patients or members of the public were involved in this study, and the study will not specifically include additional stakeholder engagement as the methods and processes being reviewed are already well established.

Contributors Design of the protocol—RP, SC and SMM. Draft of the manuscript—RP. Review and final approval of the manuscript—RP, SC and SMM.

Funding This work was supported by funding from the Digital Health Cooperative Research Centre (DHCRC-0058) and SMM is supported by an National Health and Medical Research Council administered fellowship (#1181138). The funders had no role in study design or decision to submit for publication.

Competing interests All authors have completed the Unified Competing Interest form (available on request from the corresponding author) and declare no support from any organisation for the submitted work, no financial relationships with any organisations that might have an interest in the submitted work in the previous 3 years and no other relationships or activities that could appear to have influenced the submitted work.

Patient consent for publication Not required.

Provenance and peer review Not commissioned; externally peer reviewed.

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