Predictive risk models to identify people with chronic conditions at risk of hospitalisation

Executive Summary

A disproportionately large percentage of health care costs and utilisation is spent on a small fraction of the population with complex and chronic conditions. It is widely agreed that effective and accessible primary health care (PHC) is central to reducing potentially avoidable hospitalisations (PAHs) associated with chronic disease.

Predictive risk modelling is one method that is used to identify individuals who may be at risk of a hospitalisation event. The Predictive Risk Model (PRM) is a tool for identifying at-risk patients, so that appropriate preventive care can be provided, to avoid both exacerbation and complications of existing conditions, and acute events that may lead to hospitalisation. This Policy Issue Review identifies a selection of currently available PRMs, focusing on those applied in a PHC setting; and examines evidence of reliability in targeting patients with complex and chronic conditions.

Key findings

Fifteen PRMs were included in this review: 11 International, four Australian. Findings demonstrate the difficulty in comparing results across different studies of predictive risk modelling. Hospitalisation events are commonly the main target of PRMs examined in this review but there is a substantial difference between the types of hospitalisation events used as outcomes (i.e. hospitalisation for specific condition; re-admission; emergency admission).

Performance of PRMs is highly cohort-dependent. PRMs vary in terms of the event they predict, the time period over which they predict risk, the statistical methods and reporting used and the patient predictor variables they include. PRMs targeting specific populations (as opposed to the general population) typically are more accurate as they pre-select variables with a greater likelihood of readmission and perform better statistically. For example, models that focus on ambulatory care sensitive conditions (ACSC) are likely to be more effective as selection of a condition relates to common patterns of multiple admissions over time.

Measures of performance vary across models. Evidence of high performance of PRMs was based on a c-statistic of ≥0.8, which represents the tool’s ability to differentiate high- and low-risk individuals. The c-statistic is a standardised measure which allows comparison across models. Additional evidence of model performance was included where available (e.g. Positive Predictive Value (PPV)).
which reflects the proportion of patients who are identified by the model as being ‘high risk’ and then go on to actually experience the outcome being predicted. However, the PPV is limited in terms of comparison across studies.

**Thresholds chosen for risk contribute to the accuracy of the models.** The PPV is highly dependent on a specified threshold of risk. Although most models achieve a respectable PPV by selecting only the highest risk cases (i.e. the top 1%), PPV declines rapidly when lower thresholds, broader populations or longer periods of prediction are applied to models. However, this may be sufficient in real-world terms if there is a need to rationalise the use of more expensive interventions for a small selection of people in greatest need.

**Predictor variables included in models vary depending on target population and outcome.** Most models used demographic characteristics (e.g. age and gender), specific medical diagnoses and health service utilisation (e.g. emergency admissions). Prediction within models often improved with the addition of morbidity and pharmacy data. Three models are derived from the UK’s Combined Predictive Model (CPM) algorithm applied across different settings. Unique to the CPM is a complex comorbidity predictor. Most models utilised hospital-level data. Very few PRMs specifically addressed PAHs. Four models that specifically targeted ACSCs or the elderly included a measure specific for chronic disease (e.g. Charlson Comorbidity Index), or clusters of disease recognising the complexity of chronic disease and prevalence of multimorbidity. Patient-specific variables, such as marital status as an indicator of social support, were also important predictors across several models. Very few models identified modifiable variables (e.g. obesity, smoking), which could be included in targeted interventions.

**It is impossible to evaluate a model away from its application** – and it is the latter that is the challenge. Validation of a model is critical to test its ability to correctly identify the people most at risk. PRMs used in a PHC setting differ from those used in a hospital setting in terms of outcomes, thresholds targeted for intervention (intermediate vs high risk) and data sources.

**Secure, reliable, available data are required across systems and sectors.** Legal and ethical implications need to be considered as sensitive person-level health care data are required to populate these models; particularly where there is a lack of model transparency, and where a model indicates preference for care provision that excludes sectors of the population (e.g. on basis of gender). For example, one way to protect confidentiality is through the use of pseudonymised data, which can only be unscrambled by a patient’s GP to identify their risk score.

**Statistical accuracy is only one aspect of model suitability.** Caution is needed when reviewing evidence for models. There is a series of proprietary PRMs with high levels of investment tied up in presenting results of analyses of predictive accuracy in a favourable light. Other important factors to consider include costs, time and resource intensity, and ease of use. Three models were included that were based on widespread implementation (CPM, LACE and PRISM\(^2\)). Although these were not the highest performing models based on statistical parameters, there was little difference in their statistical performance as most of them incorporate similar sets of variables to predict similar events. Moreover, if implementation is overly complicated, resource intensive, or viewed as an impediment to service delivery, it is likely that users will abandon the programme irrespective of its predictive accuracy.

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1. LACE: Length of stay, Acuity of admission, patient Comorbidity, and number of visits to the Emergency room.
2. PRISM: Predictive Risk Stratification Model.
There is little available information on the costs of introducing risk models. Two trials are underway which have targeted costs as a research outcome (PRISM in Wales and SPOKE\(^3\) in Sussex). There are substantial cost implications related to: investment in infrastructure for model development and maintenance; development and/or procurement costs associated with adaptation to settings; and ongoing maintenance to maintain accuracy and reliability. Models also require a combination of hospital and PHC data; and good linkage of datasets between primary and secondary care settings. There may also be added value from software tools that enable risk management across the spectrum (i.e. before diagnosis of a chronic condition). Purpose-built models that use routinely available data ensure that they can be implemented in a variety of health care settings without adding excessive burden for data collection and management.

**Policy considerations**

PRMs may be useful tools for predicting risk of hospitalisation in certain circumstances. However, they should only be considered as part of a broader strategy for chronic disease management. In terms of the Australian health care system and approaches to identification of those with chronic disease and at greatest risk for hospitalisation, the following factors may be considered before investing in, or implementing, a particular model:

- Each model, and its application, needs to be taken on its own merits. There is no clear advantage of using one tool over another.
- PRMs are tools for case-finding; before determining which tool may be the best fit, it is important to clarify the type of admission being targeted, the population of interest, and the purpose or intent.
- Investment in PRMs is likely to be substantial. At the system level, options include procuring an established model and modifying it to meet local needs, or building an entirely new model for the local or regional Australian setting. Commercially available versions may be more difficult to modify as details of the variables and algorithms are not always accessible.
- Readmissions are easier to predict than admissions.
- Predicting risk for hospitalisation in the subsequent year in a general population sample is much more difficult as there is more variability - therefore less accurate.
- Models should target predictors of PAHs (e.g. age, social deprivation, morbidity) to improve accuracy and identify relevant variables that are modifiable. This can inform more targeted interventions.
- Routinely available data ensure that PRMs can be implemented in a variety of health care settings without adding excessive burden with data collection and management.
- To improve performance of models, detailed data on individual patients need to be available. Reliable, up-to-date, locally-relevant data are critical for the accuracy and relevance of using PRMs to target particular outcomes.
- Clarity and consistency of disease coding is essential.
- Widely implemented PRMs generally include data on social factors; this requires reliable data linkage across health and social care, particularly for use of PRMs in PHC settings.
- Robust processes, procedures and information technology are critical to protect privacy and confidentiality as sensitive person-level health care data are needed to populate these models.
- Other factors also impact on admissions and thus the predictive ability of PRMs. For example, systemic variation in health service provision may influence accessibility to health care (e.g. after hours PHC, distance from emergency department).

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\(^3\) SPOKE: Sussex Predictor of Key Events.
Method

A rapid review was conducted to examine the evidence pertaining to the effectiveness of PRMs for identifying patients with complex and chronic conditions who may be at risk of PAHs. This pragmatic review involved a search and synthesis of relevant peer reviewed and grey literature restricted to the period from 2009 to 2014. Included studies were limited to those providing details on PRMs that predicted hospital admissions, readmissions and emergency admissions in the following settings: Australia, Canada, United Kingdom, New Zealand, and the United States.

For more details, see Full Report.