Targeting integrated care to those most likely to need frequent health care: a review of social and clinical risk factors

Janet E. Sansoni  
*University of Wollongong, jans@uow.edu.au*

Pamela E. Grootemaat  
*University of Wollongong, pamg@uow.edu.au*

Habibur R. Seraji  
*University of Wollongong, habibur@uow.edu.au*

Megan B. Blanchard  
*University of Wollongong, mblancha@uow.edu.au*

Milena Snoek  
*University of Wollongong, milena@uow.edu.au*

Publication Details

Targeting integrated care to those most likely to need frequent health care: a review of social and clinical risk factors

Abstract
Evidence check: Targeting integrated care: social and clinical risk factors

Keywords
factors, most, social, those, care, review, integrated, targeting, health, clinical, frequent, need, risk, likely

Publication Details
J. Sansoni, P. Grootemaat, M. Seraji, M. Blanchard & M. Snoek, Targeting integrated care to those most likely to need frequent health care: a review of social and clinical risk factors (Sax Institute, Australia, 2015).

This report is available at Research Online: http://ro.uow.edu.au/ahsri/668
Targeting integrated care: social and clinical risk factors
An Evidence Check rapid review brokered by the Sax Institute for the NSW Agency for Clinical Innovation
May 2015

This report was prepared by:
Janet Sansosi, Pam Grootemaat, M Habibur Seraji, Megan Blanchard, Milena Snoek

May 2015
© Sax Institute 2015

This work is copyright. It may be reproduced in whole or in part for study training purposes subject to the inclusions of an acknowledgement of the source. It may not be reproduced for commercial usage or sale. Reproduction for purposes other than those indicated above requires written permission from the copyright owners.

Enquiries regarding this report may be directed to the:
Manager
Knowledge Exchange Program
Sax Institute
www.saxinstitute.org.au
knowledge.exchange@saxinstitute.org.au
Phone: +61 2 91889500

Suggested Citation:

Disclaimer:
This Evidence Check Review was produced using the Evidence Check methodology in response to specific questions from the commissioning agency.

It is not necessarily a comprehensive review of all literature relating to the topic area. It was current at the time of production (but not necessarily at the time of publication). It is reproduced for general information and third parties rely upon it at their own risk.
Targeting integrated care to those most likely to need frequent health care: a review of social and clinical risk factors

An Evidence Check rapid review brokered by the Sax Institute for the NSW Agency for Clinical Innovation
May 2015

This report was prepared by Janet Sansosi, Pam Grootemaat, M Habibur Seraji, Megan Blanchard, Milena Snoek
# Contents

List of figures ..................................................................................................................................................................................... 5  
List of tables ...................................................................................................................................................................................... 5  
List of acronyms ............................................................................................................................................................................... 5  
1 Executive summary ..................................................................................................................................................................... 7  
2 Introduction .................................................................................................................................................................................. 9  
3 Search strategy ......................................................................................................................................................................... 11  
3.1 Article review process ..................................................................................................................................................... 12  
4 Results ......................................................................................................................................................................................... 13  
4.1 Socio-demographic and social risk factors .............................................................................................................. 14  
4.1.1 Socio-demographic factors ..................................................................................................................................... 14  
4.1.2 Social factors: social support, living alone and marital status ....................................................................... 20  
4.2 Clinical risk factors ........................................................................................................................................................... 21  
4.3 Prior utilisation factors .................................................................................................................................................... 36  
5 Social and clinical risk factor summary .............................................................................................................................. 38  
6 Disease specific risk stratification approaches ................................................................................................................ 41  
   Cardiovascular disease models ............................................................................................................................................ 41  
   Other disease groups .............................................................................................................................................................. 42  
   Chronic disease management interventions .................................................................................................................... 42  
   Conclusion .................................................................................................................................................................................. 43  
7 Selecting or developing a generic model ........................................................................................................................... 44  
8 Integrated care programs and risk stratification ............................................................................................................ 46  
9 Conclusion .................................................................................................................................................................................. 54  
10 References ................................................................................................................................................................................ 56  
11 Appendices .............................................................................................................................................................................. 70  
   Appendix 1: Strength of evidence ..................................................................................................................................... 70  
   Appendix 2: Risk stratification and integrated care interventions ........................................................................... 71
List of figures

Figure 1  Risk of hospital admission and cost distribution for a GP practice in the UK……………………........... 10
Figure 2  PRISMA flow chart of study selection………………………………………………………………………………… 13
Figure 3  Relationship between the number of chronic conditions people have and average cost in the previous year ………………………………………………………………………………………………………………… 24
Figure 4  Mean number of emergency unplanned admissions by number of chronic conditions……… 24

List of tables

Table 1  Search results from academic database searches………………………………………………………………… 11
Table 2  Socio-demographic and social risk factors……………………………………………………………………………15
Table 3  Clinical risk factors…………………………………………………………………………………………………………22

List of acronyms

A&E  Accident & emergency
ACAT  Aged Care Assessment Team
ACG  Adjusted clinical groups
ACI  Agency for Clinical Innovation
ACP  Anticipatory care plan
ACSC  Ambulatory care sensitive conditions
ADL  Activities of Daily Living
AIHW  Australian Institute of Health and Welfare
AUC  Area Under Curve
BMI  Body mass index
CABG  Coronary artery bypass graft surgery
CALD  Cultural and linguistic diversity
CCG  Clinical Commissioning Group
CEHSEU  Clinical Epidemiology and Health Service Evaluation Unit
CHA  Choices for Healthy Aging
CHF  Congestive heart failure
CKD  Chronic kidney disease
CMHCB  Care Management for High-Cost Beneficiaries
COPD  Chronic obstructive pulmonary disease
CPM  Combined Predictive Model
CSCSU  Central Southern Commissioning Support Unit
CVD  Cardiovascular disease
DPoRT  Diabetes Population Risk Tool
EAM  ED admission and mortality
EARLI  Emergency Admission Risk Likelihood Index
ED  Emergency department
FEV  Forced expiratory volume
GP  General practice
HARP  Hospital Admission Risk Program
HbA1c  Haemoglobin A1c
HR  Hazard ratio
HRQOL  Health-related quality of life
ICCS  Integrated care coordination service
IHD  Ischaemic heart disease
INR  International Normalised Ratio
ISAR  Identification of Seniors At Risk
JHU  Johns Hopkins University
LACE  Length of stay, Acuity of admission, Charlson comorbidity score and ED visit
LOS  Length of stay
MCS  Mental Health Component Score From Short Form-36 Scale
MGH  Massachusetts General Hospital and the Massachusetts General Physicians Organization
NHS  National Health Service
NZ  New Zealand
PARR  Patients At Risk of Rehospitalisation
PCS  Physical Health Component Score From Short Form-36 Scale
PEONY  Predicting Emergency admissions Over the Next Year
PPH  Potentially preventable hospitalisation
Pra  Probability of repeated admissions
RCT  Randomised controlled trial
RR  Relative risk
SES  Socio-economic status
SMAF  Functional Autonomy Measurement System
SPQ  Sherbrooke Postal Questionnaire
TFI  Tilburg Frailty Indicator
TRST  Triage Risk Screening Tool
UK  United Kingdom
US  United States
1 Executive summary

This rapid review\(^1\) was commissioned by the NSW Agency for Clinical Innovation (ACI) and the Sax Institute in Australia to examine the evidence concerning social and clinical risk factors which may be significant predictors of both pre-hospital and hospital service utilisation. The context is that the NSW Ministry of Health wishes to develop a NSW approach for risk stratification and patient selection that identifies people who are at risk(s) of poorer health outcome(s), and enable targeted delivery of integrated care to those who will maximally benefit.

The focus of this review is on generic risk factors and risk prediction approaches rather than disease specific approaches, although these are also briefly discussed. While the focus is on potentially preventable hospitalisations (PPH) related to ambulatory care sensitive conditions (ACSC), many of the research studies assessed hospital admissions, readmissions, and variables such as bed days and length of stay (LOS) more broadly, although most studies exclude elective admissions. Predictive risk modelling tools were also examined to identify the significant risk factors used to predict these health utilisation outcome variables.

The review of socio-demographic and social risk factors indicated that age; gender; socio-economic status (SES) or a broad measure of social disadvantage; living alone; rural and remote location; and Aboriginal and Torres Strait Islander status and ethnicity had good evidence to support their inclusion as predictors in a risk stratification system for NSW. Important clinical risk factors included comorbidity; severity of illness; the presence of key diagnoses; self-rated health; falls history; functional status; physical activity/inactivity; long-term disability; cognitive impairment; and multiple medication use. Biomedical markers (e.g. blood pressure) were more relevant and more significant in disease specific risk prediction models rather than generic or whole of population models, and there were some conflicting findings concerning BMI. Some factors, such as smoking status and risky alcohol consumption, should be considered for inclusion, but we noted some measurement issues that needed to be addressed in considering such factors.

Some of these factors (e.g. functional status, cognitive impairment) were more often included in models predicting outcomes, such as readmission and LOS, than PPH or hospital admission. Thus, for each desired outcome, the best predictors may be slightly different, and any model utilised would need to be adjusted in relation to the particular outcome being assessed. Overall, this evidence check largely supports the potential risk factors that were identified by the ACI\(^2\) risk stratification discussion paper.

While we agree with ACI\(^2\) that no existing predictive risk stratification model is currently suitable to the NSW context, we noted that there are a number of existing models that could potentially be adapted to fit this context. Thus, we feel that some of these models could be explored in more depth, including their suitability in the Australian context. There is now a wide variety of risk prediction models available, although all of them require further and ongoing validation. There is a need to consider the relative costs of model adaptation and development.

Some of the more sophisticated ‘whole of population’ models would require the establishment of a data linkage platform that would include primary care data, A&E data, inpatient data, outpatient data, pharmaceutical data and possibly community services data. Development of such a platform would require a considerable economic investment given the lack of existing system-wide primary care data collections,
and one suspects this may take some time to develop. In the interim, we have suggested a number of simpler or ‘pilot’ strategies, supported by the evidence, that could be used to trial risk stratification methods (using some data linkage elements) to predict admission with the elderly cohort or with respect to the prediction of readmission and LOS.

A second component of this review was to examine the evidence relating to the outcomes of risk stratified integrated care interventions. This review found that there was very limited evidence that risk stratification associated with integrated care interventions systematically produced better system level outcomes, such as reduced ED visits, hospital admissions, readmissions or LOS. Despite a few positive findings, the evidence to date is not convincing and there are inconsistent findings. Admittedly, this is a new field of research, but this may also reflect the nature of evidence to support the effectiveness of integrated care interventions in general. This has shown only modest benefits in some specific areas to date. Given this, we feel that the investment required for building a ‘whole of population’ model would be hard to justify for the purposes of just targeting integrated care interventions, particularly when the evidence to support these interventions is modest. The National Health Service (NHS) has suggested a broader range of applications for data arising from such ‘whole of population’ models, such as population health profiling, disease analysis, planning, budgeting, and funding distribution/resource allocation. Given the potential costs of developing or modifying a predictive risk model, these additional benefits need to be carefully considered.

As Lewis et al. commented, the predictive accuracy of many risk stratification tools is only moderate. Thus, one needs to consider the adverse effects of false positive and false negative results, as well as the benefits of true positive and true negative results, when targeting interventions. Otherwise, targeted individuals may receive programs that are not appropriate to them or fail to receive programs or interventions that would have been appropriate for them. The benefits of any model must outweigh the costs. Currently, many of the interventions offered in risk stratification programs appear to increase cost and relatively few interventions have offset these costs with a reduction in admission or health care utilisation. As there is a lack of robust evidence to support risk stratified integrated care interventions, it is clear that further research and refinements to these approaches are required.
2 Introduction

This rapid review was commissioned by the NSW Agency for Clinical Innovation (ACI) and the Sax Institute in Australia to examine the evidence concerning social and clinical risk factors which may be significant predictors of both pre-hospital and hospital service utilisation. The context is that the NSW Ministry of Health wishes to develop a NSW approach for risk stratification and patient selection that identifies people who are at risk(s) of poorer health outcome(s), and enable targeted delivery of integrated care to those who will maximally benefit.

A current evidence check on these risk factors is relevant to the consideration of the selection and/or development of predictive risk stratification approaches/models to identify those at risk of health deterioration and hospitalisation, and to target people who may potentially benefit from integrated/coordinated care interventions. This may include interventions aimed at reducing potentially preventable hospitalisations (PPH) or ambulatory care sensitive conditions (ACSC) where it has been estimated that some reductions in admissions could be made with more effective primary care management. PPH admissions can be classed as vaccine preventable, acute or chronic. The focus of this review is on PPH for those with chronic and long-term conditions, although it is noted that vaccine preventable admissions can also be a major cause of PPH for older people. This review will not include a review of integrated/coordinated care interventions per se, but will examine studies where predictive risk modelling has been used to identify or select individuals to receive an integrated care intervention and the resulting evidence concerning the effectiveness of these particular interventions.

The Kaiser Permanente Medical Care Program has long used an integrated model of care, including inpatient and outpatient care, with the identification and active management of high-risk patients, the use of intermediate care and self-care and medical leadership. The comparison of hospital bed utilisation across the National Health Service (NHS) and Kaiser Permanente California indicated substantially less hospital utilisation for the Kaiser group, which stimulated interest in its integrated care and case management approaches. This included tuning the intensity and type of its integrated care management approaches for chronic disease by the level of risk for hospitalisation. The small percentage of very high-risk and complex patients would receive more active case management, high-risk patients would receive disease management programs, and the remaining 70–80% of chronic disease patients would receive supported self-care interventions.

It can be useful to think of target groups at a broader population level in relation to their complexity and likelihood for hospital admission. Variants of the Kaiser Permanente pyramid/triangle can, for example, segment the risks and costs associated with hospital utilisation for a primary care population (see Figure 1). This shows that the top 5% are high-risk patients for hospitalisation who can consume 27% of the costs, and thus they may need more intensive or proactive case management and care coordination interventions. By contrast, 80% of patients may be considered at lower risk of hospitalisation and consume only 48% of costs, so health promotion and prevention activities may be more suitable for this risk strata.

Targeting the appropriate level of integrated care intervention for patients is important – it would be costly and undesirable to target intensive case management interventions for those at low risk who have less need
for such interventions. However, it is important not to ignore those with moderate levels of risk (15%) as they are a group likely to represent future admissions and may be sensitive to evidence-based interventions addressing their key risk factors. They may become more vulnerable to hospitalisation if these risk factors are not addressed.

Figure 1: Risk of hospital admission and cost distribution for a GP practice in the UK

<table>
<thead>
<tr>
<th>% of patients</th>
<th>No. of patients</th>
<th>% of cost</th>
<th>Nature of Morbidity</th>
<th>Potential Intervention</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>100</td>
<td>10%</td>
<td>High-risk – multiple (3%), frail, social care needs</td>
<td>Intensive case management</td>
</tr>
<tr>
<td>4%</td>
<td>400</td>
<td>17%</td>
<td>High-risk – multiple LTC, less unstable, some social care needs</td>
<td>Case management &amp; disease management</td>
</tr>
<tr>
<td>15%</td>
<td>1500</td>
<td>25%</td>
<td>Moderate-risk – one or two chronic illnesses and/or risk factors, health likely to deteriorate over time</td>
<td>Condition management, health coaching &amp; lifestyle management</td>
</tr>
<tr>
<td>80%</td>
<td>8000</td>
<td>48%</td>
<td>Low-risk – morbidity due to timelimiting or acute illness rather than chronic conditions, patients at risk of developing chronic conditions</td>
<td>Health education, health promotion &amp; prevention strategies, lifestyle change programmes</td>
</tr>
</tbody>
</table>

Source: Johns Hopkins University (ACG) 10

Risk stratification for the selection of patients for integrated/coordinated care programs can be based on clinical knowledge (physician identification), be criteria/threshold based (e.g. include patients over 65 with an index admission for a chronic disease), or can be based on predictive models derived from statistical analysis of system level health utilisation and claims/cost data. The focus of this review is more on the latter approach as the evidence suggests predictive risk modelling approaches have generally been found to be more accurate in identifying those who might benefit from integrated/coordinated care 11-14, and they have been used extensively in the UK and the US. However, in order to develop a risk stratification model or approach, one must first consider the evidence supporting the risk factors that are contained in these models. In the review, we will discuss social and clinical risk factors that have been found to be significant predictors of health service utilisation. The focus of the review is largely on whole of population models or approaches that use targeted groups (elderly, those with chronic and long-term conditions) rather than disease specific risk stratification approaches, but these will also be briefly discussed. The outcomes of integrated care interventions, where predictive risk modelling has been used for patient selection, will be examined.
A ‘rapid’ review using a comprehensive search strategy was implemented to identify research articles relating to risk assessment and integrated care. To identify peer-reviewed literature, the following academic databases were used: MEDLINE, PsycINFO, CINAHL, Scopus, ProQuest and Cochrane Collaboration. Terms were developed from the ACI/Sax Institute proposal and in conjunction with University of Wollongong librarians. The following search strategy was used to identify relevant articles:

1. ‘primary care’ or GP or ‘General Practic*’ or hospital or ‘Emergency Department*’ or ‘health service’ or outpatient or ‘community health’, AND
2. tool* or index* or model, AND
3. ‘risk predict*’ or ‘risk stratification’ or ‘risk prevent*’, AND
4. ‘complex and chronic conditions’ or ‘integrated care’ or age* or disab* or ‘coordinated care’ or ‘chronic disease’ or diabet* or ‘cardio vascular’ or comorbid*.

Additional terms were used with the Scopus database to further target the search, including admission* AND ‘length of stay’.

The search was limited to English language and humans and year=’2005–2015’ and ‘all adult (19 plus years)’ and country (Australia or ‘United States of America’ or US or UK or ‘United Kingdom’ or Canada or ‘New Zealand’ or Europe). Peer-reviewed journal articles, books and book chapters, theses and reports were included in the search. Table 1 provides an outline of search results for each database.

<table>
<thead>
<tr>
<th>Database</th>
<th>Initial results</th>
<th>Kept after title and abstract review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medline</td>
<td>139</td>
<td>60</td>
</tr>
<tr>
<td>CINAHL</td>
<td>208</td>
<td>18</td>
</tr>
<tr>
<td>PsychInfo</td>
<td>23</td>
<td>2</td>
</tr>
<tr>
<td>Scopus</td>
<td>103</td>
<td>40</td>
</tr>
<tr>
<td>ProQuest</td>
<td>247</td>
<td>43</td>
</tr>
<tr>
<td>Cochrane</td>
<td>88</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>808</td>
<td>164</td>
</tr>
</tbody>
</table>

The most effective search terms from the database searches were also used with internet search engines such as Google and Google Scholar to identify relevant material, including grey literature. Search techniques, such as snowballing and reference list searching, were also used. Reports, websites, web pages, electronic articles, journal articles, books and book chapters were included.

Articles were exported into EndNote for citation management. Duplicate references were removed. Articles were then reviewed for possible inclusion in the review. The following criteria were used to identify articles for their possible inclusion in the review:

- Australian and international published peer-reviewed literature
• Literature published from 2005 to the present that was written in English. However, where information from earlier literature was identified as relevant, this was also included.

3.1 Article review process

Articles and documents identified for inclusion in the review were independently rated by two researchers using the following criteria:

• Strength of evidence (see Appendix 1)
• Significance of effect (articles were summarised for each study identified and the significance levels of the major findings were recorded).

Where disagreement occurred, these abstracts were checked by a third staff member and consensus reached.

Articles were categorised and entered into spreadsheets with the following column headings: author, date, title, reviewer, relevance according to inclusion criteria, study design, strength of evidence, study number, study summary and any further comments. This allowed articles to be analysed using common criteria.

Articles were then further categorised into topics emerging after initial assessment, including integrated care models and research, risk factors and disease specific assessment. Articles were entered into topic specific spreadsheets to allow for analysis within the topic area. The researchers held regular team meetings to discuss the content and direction of the review.
4 Results

A total of 1064 records were identified through database and other searches for possible inclusion in the review. Of these, 421 documents were retrieved. Some articles were found to be of marginal or limited relevance upon reading and were rejected. Figure 2 below provides an outline of the study selection process in the form of a PRISMA diagram for the reporting of literature reviews.15 Among the remaining articles, 256 related to social and clinical risk factors which may be significant predictors of both pre-hospital and hospital service utilisation and studies that examined interventions associated with risk stratification.

Of those studies and reviews included in this review, 211 articles were classed as academic literature, including journal articles and Cochrane reviews, and 45 documents were grey literature, such as reports, conference papers, web documents or websites. The majority of articles were published from 2005 to the time this review was undertaken. Most of the material included was published in the US or the UK but also included literature from Europe, Australia, Canada, New Zealand, Japan and Israel.

*Figure 2: PRISMA flowchart of study selection*

Based on this search strategy, the following sections outline the evidence concerning socio-demographic and clinical risk factors for admission to hospital and associated outcomes.
4.1 Socio-demographic and social risk factors

4.1.1 Socio-demographic factors

The most commonly assessed socio-demographic predictor variables for ED visits and hospital admissions were age, age band or group, gender, SES, income education, social deprivation, Aboriginal and Torres Strait Islander status, CALD or immigrant status, ethnicity and rural or remote location (see Table 2).

Most of the empirical studies that examined socio-demographic and social factors were ranked as being of ‘acceptable practice’ or better with regard to their strength of evidence rating (see Appendix 1). Only three studies were rated as ‘emerging practice’\(^{16-18}\). These are discussed in the text below but are not included in the summary table. Many studies concerning the predictive risk models analysed large databases of health system administrative data and we classed these studies as ‘other’. However, as they all involved either historical comparisons (e.g. before and after comparisons across years of retrospective administrative data) or used retrospective and prospective data, they were considered to be ‘acceptable practice’ or better. Review articles were not included, but where relevant a remark (see ‘comment’ or ‘other’) was made.
### Table 2: Socio-demographic and social risk factors

<table>
<thead>
<tr>
<th>Socio-demographic and social risk factors</th>
<th>Comment</th>
<th>Degree of effect</th>
<th>Strength of evidence</th>
<th>Relevant studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Bimodal distribution with those over 65 years and below 19 years having higher rates of hospitalisation. Interaction effects – older males more PPH. Included, and a significant predictor, in most risk stratification models. Important for risk adjustment purposes when making comparisons. Effect may vary by disease type.</td>
<td>Strong</td>
<td>Very strong</td>
<td>Positive findings: 7,24,25,26,27,29,31,32,33,34,35, 37,38,39,40,36,37,40,41,42,44,45,47,50,77  Null/ contrary findings: 46,55  Other: One disease specific review &amp; one review concerning older ED patients reported null findings.</td>
</tr>
<tr>
<td>Gender</td>
<td>Some evidence for males to have higher rates of PPH admission for some conditions. Interaction effects by type of disease or condition, age, SES and rurality. Included in most risk stratification models and important for risk adjustment purposes when making comparisons.</td>
<td>Moderate interaction effects</td>
<td>Moderate</td>
<td>Positive findings: 37,44,53,58,57,58,60,61,62, 63,64,65,66,77  Null/contrary findings: 55</td>
</tr>
<tr>
<td>Socio-economic status and disadvantage</td>
<td>Lower SES and broader indicators of disadvantage are highly related to hospital admission. Earlier Ansari review showed that another 21/23 studies indicated a significant effect.</td>
<td>Strong</td>
<td>Very strong</td>
<td>Positive findings: 35,45,57,59,72,73,74,75,76,77,78, 79,80,81,82,84  Other: Plus 21 early studies reported by Ansari  Null/contrary findings: Ansari reported 2 null findings</td>
</tr>
<tr>
<td>Education (alone)</td>
<td>Education may be included in a social disadvantage variable – relatively few studies examined education alone and there were some equivocal findings. Education usually not included, or actively excluded, in predictive risk models.</td>
<td>Weak to moderate</td>
<td>Weak</td>
<td>Positive findings: 46,70,71,72,73  Null/contrary findings: 55  Other: Reviews of models indicate education is rarely included. Muenchberger et al. found 5/9 studies significant but no direct citation was provided.</td>
</tr>
<tr>
<td>Rurality</td>
<td>A strong factor for Australia, but some non-linear patterns also reported. Ansari review reported 13/14 earlier studies found this a strong predictive factor. May well reflect primary care access but the effect remains after adjustment.</td>
<td>Strong</td>
<td>Strong</td>
<td>Positive findings: 56,57,79,81,82,83,84,85  Non-linear findings: 45,60,83  Other: Ansari reported 13 other significant early findings that are not included above.</td>
</tr>
<tr>
<td>Marital status</td>
<td>Rarely studied and may be a poor proxy variable associated with living alone. Included in a few predictive models. No consistent evidence.</td>
<td>Weak</td>
<td>Limited evidence</td>
<td>Positive findings: 28,28  Null/contrary findings: 92, 102</td>
</tr>
<tr>
<td>Social support/living alone</td>
<td>Living alone is often used as a proxy for the absence of adequate social support. However, the strongest evidence came from research studies which explored social support in more depth. Generally, living alone is a predictor of hospitalisation and particularly readmission, but there are some equivocal findings.</td>
<td>Moderate to strong</td>
<td>Moderate</td>
<td>Positive findings: 47,51,72,79,104,105,106,107,109,110  Null/contrary findings: 92,108</td>
</tr>
<tr>
<td>Living arrangements/household composition</td>
<td>Rarely studied and inconclusive findings to date, but it is included in the APHID (Assessing Preventable Hospitalisation Indicators) study. This requires further investigation.</td>
<td>Weak</td>
<td>Weak</td>
<td>Positive findings: 106,113  Null/contrary findings: 45</td>
</tr>
<tr>
<td>CALD/immigrant status</td>
<td>Rarely studied with some conflicting findings (sometimes higher rates of admissions and sometimes lower rates), so this requires further exploration. May be useful to include for planning purposes.</td>
<td>Unclear &amp; rarely studied</td>
<td>Limited evidence</td>
<td>Positive findings: 57,70,101  Null/contrary findings: 64,92</td>
</tr>
<tr>
<td>Ethnicity including Aboriginal and Torres Strait Islander status</td>
<td>There are substantial data indicating increased rates of hospitalisation for Australian Indigenous peoples. US studies concerned higher hospitalisation rates for African Americans or people of Hispanic extraction.</td>
<td>Strong</td>
<td>Strong</td>
<td>Positive findings: 35,56,77,81,82,86, 87,88,89,90,91,92,93,94,95,96,97,98,99,100,141  Null/contrary findings:</td>
</tr>
</tbody>
</table>
Age

The major review studies report a strong effect for age as a predictor of hospital admission and ED visits, particularly with respect to groups 65 years and over.\textsuperscript{19–23} It should be noted, however, that age has a U-shaped distribution, with more hospital admissions for those under 19 as well as for those over 65.\textsuperscript{19,24,25} Tian et al.\textsuperscript{7} noted that PPH rates in the UK were highest for those under 5 and over 75.

Other empirical studies also note age effects.\textsuperscript{24–35} Most predictive models include age\textsuperscript{27,30,36,37}, and some\textsuperscript{18,38–40} analyse effects by elderly age bands. Chenore et al.\textsuperscript{39} noted that the age bands of 85–89, 90–94 and 95+ were three of the most powerful predictors of admissions in the Devon Predictive Model. Most predictive models include age either as a predictor or for risk adjustment purposes\textsuperscript{10,19,27,36,39,41,42} when comparisons are made. Some predictive models only focus on the older age groups, such as those over 75 years\textsuperscript{28,38,43}, and earlier Australian data\textsuperscript{20,44} noted higher PPH rates for those over 75 years.

Rizza et al.\textsuperscript{45} noted interaction effects between age and gender, with higher rates of PPH being reported for older males. Tian et al.\textsuperscript{7} noted that the gap between the PPH rate for males and females in the UK increases from the 50–54 age bands. There may also be interaction effects by disease; Diette et al.\textsuperscript{46} did not find an age effect for admissions with asthma, so age effects may vary by the particular disease under consideration.

With respect to readmission and length of stay (LOS), age has also been investigated as a strong predictor.\textsuperscript{18,47–54} Aminzadeh et al.\textsuperscript{47} found in their review that older persons had longer ED stays. It is difficult to ascertain the role of age bands (mentioned above) on readmission, as Chenore et al.\textsuperscript{39} in their predictive model did not separate readmissions from other admissions, although Loren-Guerrero et al.\textsuperscript{18} found that age over 80 years was a significant predictor.\textsuperscript{18} De Buyser et al.\textsuperscript{50} in their analysis of predictors of hospital outcome, including LOS, concluded that older age is a strong predictor when accompanied by decreased physical function and malnutrition. Similarly, studies by Loren-Guerrero et al.\textsuperscript{18}, Lopez-Aguila et al.\textsuperscript{52}, and Imison et al.\textsuperscript{54} showed that age is a predictor of hospital bed use and LOS\textsuperscript{18,52,54} in elderly patients. In another study concerning the LACE+ index, it was found that age, along with other factors added to the LACE index, resulted in higher predictive power for urgent readmission.\textsuperscript{53} However, age was not found to be a strong risk predictor of rehospitalisation in older ED patients\textsuperscript{55}, but this review only considered age within elderly samples, and in patients with COPD\textsuperscript{70} and chronic heart failure.\textsuperscript{46} As mentioned above, this suggests that the role of age in risk prediction for readmissions may be dependent on the underlying disease conditions.

Population health studies\textsuperscript{56–58}, however, indicate that some common risk factors such as current daily smoking and heavy/risky alcohol consumption are less prevalent in the older age groups, and thus preventive interventions focusing on such lifestyle factors may not be as pertinent for these groups.

Gender

A review by Muenchberger et al.\textsuperscript{22,23} identified that 16 out of 21 studies reported significant effects of gender in relation to admissions, but it mainly discussed 5 studies\textsuperscript{59–63} reporting substantial gender effects by type of disease (asthma, COPD, diabetes).\textsuperscript{23} Gender may also interact with disease/health condition, age, SES and ethnicity in relation to PPH or ACSC admissions.\textsuperscript{54,65} Trawick et al.\textsuperscript{63} found that high-risk female patients for asthma were admitted twice as often as high-risk males and were older. Earlier Australian data\textsuperscript{44} had indicated a higher rate of PPH for males. Li and Hempstead\textsuperscript{66} reported that with regard to circulatory
and respiratory conditions, female PPH rates are higher than male rates for asthma and hypertension, angina, and for those aged 65–74 years. However, male rates are higher for COPD and congestive heart failure (CHF), both of which are major causes for admission. Katterl et al. concluded that men may be more likely to be hospitalised for some PPH conditions, but this may be moderated or confounded by other factors, and that gender has a moderate effect as a predictor of PPH.

Donnan et al. noted that male gender and age were strong and significant risk factors in the PEONY (Predicting Emergency admissions Over the Next Year) model. Most studies and predictive models for ED visits and admissions include gender as a predictor and for risk adjustment purposes. For data analysis purposes, it would seem necessary to include gender in any model.

The review of studies concerning predictive factors for readmission showed that male gender combined with history of falls and gender added to the LACE index, and resulted in higher predictive power for readmission and LOS. However, gender was not found to be a significant predictor of readmission or LOS in a study of the elderly conducted by Incalzi et al.

Population health survey studies indicate that there are some gender differentials for common risk factors associated with hospital admissions (e.g. smoking, risky alcohol use). Males tend to have more risk factors, and there are also gender interactions by disease and age which may need to be considered when targeting health promotion, prevention and integrated care programs.

**Socio-economic status including education, income and social disadvantage**

The major review articles have examined much of the earlier research. Ansari examined 23 earlier studies concerning SES and social disadvantage, and all but 2 of these studies reported an SES variable as a predictor of ACSC admission.

Muenchberger et al. reported that SES (including the variables of income and education) was found to be a strong (inverse) predictor in 39% of the total studies selected. Of studies that reported income alone, 75% indicated a significant association with avoidable hospitalisation. Muenchberger et al. reported that education alone was found to be significant in only five of nine studies identified. However, Kansagara et al. reported that education was excluded from all predictive models for readmissions presumably because it was not significant in the initial analysis. This might suggest there is an unusual distribution (e.g. a U-shaped curve) for education in relation to admissions/readmissions data which may require further exploration. Wallace et al. in a review of predictive models for admission, indicated that education alone was not included as a predictor.

Mian et al. reported that low income and lower education level were associated with a higher likelihood of ED admissions after controlling for access to family practitioners. Education level has also been found to be associated with preventable hospitalisation and readmission in a Medicaid sample. Education is more likely to be included within a measure of social disadvantage.

Broader measures of social disadvantage (e.g. education, personal income, ethnic group, neighbourhood disadvantage) have indicated that those with greater socio-economic disadvantage have more hospitalisations for avoidable conditions. Booth and Hux reported that those living in low income neighbourhoods were more likely to have hospitalisation associated with diabetes. Those in the lowest
income quartile were 44% more likely to be hospitalised than those in the highest income quartile, even after adjusting for potential confounders. Claudio et al. found that hospitalisation rates for asthma were concentrated in poor areas. West et al. found some evidence of an association between hospital admissions for falls and socio-economic deprivation, but no association was found for hip fracture. A study by Prescott et al. examined education and income combined and found that people with COPD with low SES were three times more likely to be hospitalised. Amarasingham et al. found that lower SES was a significant predictor of readmission in their model. Tsuchihashi et al. reported unemployment as a risk factor for readmission in a Medicaid cohort. Raven et al. developed a risk stratification model including social and clinical predictors for a Medicaid cohort and followed up high-risk patients who were actually admitted in the following year. For these patients, 56% cited the ED as usual point of care, 42% of their admissions were related to substance abuse, and 60% were homeless or precariously housed. Social isolation was also identified as a factor. Barnett et al. in a study of multi-morbidity found that the onset of multi-morbidity occurred 10–15 years earlier for those living in the most deprived areas. Socio-economic deprivation (residential area based) was associated with more multi-morbidity, including mental disorders.

Glover et al. reported that PPH admission rates in Australia were significantly higher in areas of greater socio-economic disadvantage compared with those of least socio-economic disadvantage (RR=1.61, p<0.01). AIHW noted that people in the lowest socio-economic group had the highest rates for cardiovascular disease (CVD), diabetes and chronic kidney disease (CKD) hospitalisations. AIHW reported in Australia’s Health that the higher the SES group, the less likely a person is to smoke (10% vs. 23%), and people living in the lowest SES areas are more likely to place themselves at harm from drinking alcohol (22% vs. 11%) and to be less physically active. Miller designed three models for risk indexes for chronic disease based on NSW health survey data and noted that socio-economic disadvantage and male gender were significant predictors for these models. Overall, there is strong evidence that SES and social disadvantage are major risk factors associated with PPH and admissions for chronic disease.

Rurality

Ansari reported on eight earlier univariate studies and six multivariate studies concerning rurality. All but one of these studies found a significant effect for rurality in relation to ACSC hospitalisations. Some studies group geographical areas (e.g. urban, regional, rural and remote), and for some of these studies non-linear associations with rurality have been reported. Purdy, for example, noted that PPH admission rates were highest for those in rural areas but were also higher for those living adjacent to a hospital in urban areas. The Mian et al. survey reported that residence in rural areas in Canada was a significant predictor of ED use, independent of access to family physicians. Ansari et al. was a Victorian study which reported a significant difference in the mean PPH rate across rural areas compared to urban areas, although there were no significant differences in the mean supply of primary care physicians across these areas. AIHW reported that those living in remote and very remote areas had the highest rates for CVD, diabetes and CKD hospitalisations. The National Health Performance Authority reported that rural Medicare Local areas had higher rates for potentially avoidable hospitalisation than regional or metropolitan areas – but this may possibly be associated with fewer primary care and community services being available in remote and rural areas.

AIHW reported that people in remote and regional Australia are more likely to smoke, be overweight or obese, indulge in harmful levels of alcohol use, be insufficiently active and have high blood cholesterol, which are all risk factors for chronic disease. Miller in her risk modelling for chronic disease, found that
survey participants from the Far West Area Health Service had significantly higher means scores on her chronic risk indices, suggesting that rurality or remoteness may be a factor.

A Katterl et al. review of some earlier international studies also examined factors such as distance to hospital which appeared to show a curvilinear trend, with those living both very close and very far from hospitals having the highest rate of hospital admissions. However, overall for Australia, a rural or remote location seems strongly associated with hospital admissions and/or PPH.

Ethnicity and race

Ansari reported six earlier studies where ACSC admissions have been higher for people from either African or Hispanic descent in the US. Katterl et al. and Muenchberger et al. mention a number of early studies, including Eisner et al. and Carr et al., that suggested ethnicity was a factor in a much higher rate of asthma admissions for African Americans or people of Hispanic extraction. Muennig et al. reported that being born in Africa or being born in Latin America predicted a higher rate of hospitalisation in New York City.

Similar findings have been reported for Maori and non-Maori in New Zealand. Duckett et al. reported high rates of hospital admissions for Aboriginal populations compared with non-Aboriginal populations in Australia, as did Condon and Banham et al. AIHW reported that Aboriginal and Torres Strait Islander peoples have higher rates of hospitalisation for CVD, CKD and diabetes. There is a significant Indigenous health gap, and Indigenous Australians also have three times the hospitalisations for respiratory conditions and more than twice the hospitalisations for mental and behavioural disorders. Social determinants (such as lack of education and unemployment) and increased risk factors for chronic disease (e.g. smoking, obesity and physical inactivity) can contribute to this health gap. Of the social determinants, household income, highest level of school completed, and employment status have the largest estimated impact on the gap (31 per cent). Smoking status, BMI, and binge drinking are the behavioural risk factors with the biggest impact (11 per cent). The interaction between social determinants and behavioural risk factors is estimated to contribute to 15% of the health gap. Other factors, such as worse access to health services, also contributed substantially to this health gap (43 per cent).

Gubhaju et al. examined social and other determinants of health status with reference to developing a risk profile for Aboriginal participants in the 45 and Up Study. The most common factors were smoking, obesity, diagnosis of diabetes, depression, stroke; and having caregiving responsibilities, a major physical disability, severe physical functional limitations and high levels of psychological distress.

ACT differentiated between complexity variables which can be considered principal factors that are highly predictive of hospitalisation (Aboriginality, age, previous admissions, chronic disease or disability, three or more medications, comorbidity) and variables that amplify risk (smoking, alcohol and drug misuse, cognitive impairment, social determinants, CALD, mental health, biomedical factors, falls history). The Gubhaju et al. study provides examples of how these primary factors and amplifying factors can interact to heighten the risks of particular population groups, as does the study by Vos et al. concerning the Indigenous health gap.

In this literature we found few studies where immigrant status had been examined. Antoniou reported that recent immigrants had lower rates of HIV admissions, and Meunnig et al. reported that zip codes with a higher proportion of foreign-born people predicted a lower rate of hospitalisation in New York City.
However, Mian et al. found that recent immigrant status was a predictor of the likelihood of increased ED use in Canada. Van Oeffelen et al. found that after the first acute myocardial infarction hospitalisation, readmission was higher for all immigrant groups. Readmission after CHF was also often higher among migrant groups.

Similarly, there was little evidence found concerning the risk factors for those from culturally and linguistically diverse backgrounds (CALD). Miller found that significant predictive factors for a survey-based chronic disease risk index were being Australian born and having English as the first language (which is probably reflecting lower rates for some risk factors in CALD groups).

4.1.2 Social factors: social support, living alone and marital status

One study reported marital status as a risk factor, but this may be that it is serving as a proxy for living alone; although single, unmarried or widowed status does not necessarily imply one is living alone. Baena-Canada et al. examined non-protocol additional services for cancer patients receiving chemotherapy and found additional service use, which included ED visits and admissions, was associated with older age and unmarried status. Eisner et al. reported that married individuals or those who were cohabiting were not significantly more at risk of hospitalisation than those unmarried or not cohabiting. Inouye et al. included unmarried status as one of five factors in their predictive model for admissions for the elderly, and Hasan et al. , Chin and Goldman, and Amarasingham et al. also included marital status in their predictive models for readmission. Green et al. found there was greater compliance with recommended exercise regimens following hospitalisation for patients with an acute coronary syndrome who lived with a partner or spouse.

Most studies focus on measures of social support and living alone. A follow-up study of the outcomes of elderly persons in the ED indicated that living alone and lack of social support were predictive of adverse outcomes (e.g. hospitalisation, ED return, functional decline, death) following discharge from the ED. Living alone was a significant predictor of hospitalisation in the following year for a community dwelling sample of elderly people using home health care service agencies in Italy. Raven et al. identified social isolation as a factor associated with frequent hospital admission in a Medicaid cohort. Aliyu et al. found that elderly people living with non-relatives were three times more likely to be admitted to hospitals than those living with their partner. Saxena et al. found that living alone was significantly related to hospital admission, but an earlier study found no significant relationship. A study by Longman et al. interviewed rural community based service providers concerning the risk of frequent and/or avoidable hospitalisation, and social isolation was repeatedly identified as an important factor for these admissions. Luttik et al. in a systematic review identified that social support was a predictor for admissions for people with heart failure and highlighted the role of partners in preventing readmissions.

A follow-up study among elderly CHF patients assigned scores for their social network found that hospital readmission was higher in patients with low and medium scores compared to patients with high scores. Three other studies reported social factors, such as living alone or living in a nursing home, as significant predictors of repeat hospital use, including early readmission and repeat ED visit. A similar relationship was reported by Loren-Guerrero et al. for living status (alone or retirement home) associated with a longer hospital stay. In another study, it was found that inappropriate hospital use days was associated with living alone. Betihavas et al. in a review comparing predictive models for CHF readmissions, reported that single marital status was predictive of readmission in more than one model. However, surprisingly, Hasan et al.
found marital status (currently married), along with six other factors, to be a significant predictor of early readmission.

There is increasing evidence that social support, or, conversely, social isolation, may be an important factor for admission, and particularly for readmission. Marital status, although available in most administrative datasets, does not appear to be an appropriate proxy for social support. Living alone or living with a partner appears to be a better proxy for lower levels of social support as the evidence is generally positive, but two early studies reported null findings. The strongest effect for social support was reported by Rodriguez-Artalejo, who examined the degree of social support in some depth, and indicates that while living alone is important, it is living alone with no family support that may be the critical issue. The recent APHID (Assessing Preventable Hospitalisation InDicators) study concerning PPH includes household composition/living alone, so further Australian data on this issue should be available shortly.

Muenchberger et al.22 and Katterl et al.21 examined studies that addressed living arrangements more broadly (e.g. household composition, crowding), but there are few studies and the evidence is equivocal. Katterl et al.21 suggest that there was a higher risk for crowding, but this may be confounded by SES and possibly may be an issue related to particular health conditions such as asthma.

4.2 Clinical risk factors

The most commonly assessed clinical predictor variables for ED visits and hospital admissions included comorbidity, severity of illness, frailty, self-rated health/health status, functional limitations and cognitive impairment, population health related risk factors (e.g. smoking, alcohol use, obesity, physical inactivity etc.) and medication use or polypharmacy (see Table 3).

Most of the studies that examined clinical risk factors were ranked as being of ‘acceptable practice’ or better with regard to their strength of evidence rating (see Appendix 1). Only eight studies were rated as ‘emerging practice’. These are discussed briefly in the text below but are not included in the summary table. Many studies concerning the predictive risk models analysed large databases of health system administrative data, and we classed these studies as ‘other’. However, as they all involved either historical comparisons (e.g. before and after comparisons across years of retrospective administrative data) or used both retrospective and prospective data, they were considered to be of ‘acceptable practice’ or better. Review articles were not included, but where relevant a remark (see ‘comment’ or ‘other’) was made.
### Table 3: Clinical risk factors

<table>
<thead>
<tr>
<th>Clinical risk factors</th>
<th>Comment</th>
<th>Degree of effect</th>
<th>Strength of evidence</th>
<th>Relevant studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Severity of health condition</td>
<td>Few studies examined this directly, but a number of studies included case mix-style groups as a proxy for severity. Severity of illness may be necessary for risk adjustment purposes where comparisons are made.</td>
<td>Moderate</td>
<td>Moderate</td>
<td>Positive findings: 10,29,30,41,53,121,139,144,145,146 Null/contrary findings:</td>
</tr>
<tr>
<td>Presence of particular diagnoses</td>
<td>Some studies identified particular diseases or conditions as increasing the risk of admission or readmission, including diabetes, CKD, IHD (ischaemic heart disease), COPD, CHF, heart problems, coronary artery disease, anaemia and mental illness</td>
<td>Moderate</td>
<td>Moderate</td>
<td>Positive findings: 10,42,43,51,77,111,120,130,139,141–144 Null/contrary findings:</td>
</tr>
<tr>
<td>Health status</td>
<td>Some models which utilised self-report data included self-rated health status and it has been found to be a significant predictor in those models. Useful in research studies or in those models which include some self-report data, but generally unavailable in administrative datasets</td>
<td>Moderate to strong</td>
<td>Moderate, but depends on measure used</td>
<td>Positive findings: 31,42,43,46,102,110,124,144,147–153,155,222 Null/contrary findings: 163 (frailty tools)</td>
</tr>
<tr>
<td>Functional status, falls, disability</td>
<td>Although included in some studies and models predicting admissions, these variables are more commonly investigated in models and studies concerned with readmission and LOS</td>
<td>Moderate to strong</td>
<td>Moderate to strong</td>
<td>Positive findings: 2,27,39,40,43,47,50,51,65,73,76,111,130,139,243 Null/contrary findings: 55,163,164</td>
</tr>
<tr>
<td>Frailty indicators and triage tools</td>
<td>For readmission there is interest in using frailty measures or indicators, but most had poor psychometric properties and poor predictive performance. NHS recommends using some frailty measures in addition to risk stratification.</td>
<td>Low</td>
<td>Low overall but there is a need to assess further evidence re suggested NHS tools</td>
<td>Positive findings: 115,130 Null/contrary findings: 163,164 Other: review by Carpenter[45], null findings</td>
</tr>
<tr>
<td>Cognitive impairment</td>
<td>Some prediction models (7/27) for admission and (7/12) models for predicting readmission included cognitive impairment. A limited number of other studies indicated this factor may have a moderate effect.</td>
<td>Moderate</td>
<td>Limited – see comments. It is recommended for elderly samples and readmission studies.</td>
<td>Positive findings: 43,127 Other: Reviews indicated this was included in 7 admission models[69] and 7 readmission models[14] as a predictor. Null/contrary findings:</td>
</tr>
<tr>
<td>Medication use</td>
<td>Numerous studies indicated this was an important risk factor and it is included in most of the leading predictive models for admissions and LOS</td>
<td>Very strong</td>
<td>Very strong</td>
<td>Positive findings: 10,12,30,37,40,42,43,55,65,122,130,139,167,168 Null/contrary findings: 173</td>
</tr>
<tr>
<td>Presence of leg ulcers</td>
<td>Limited evidence as yet</td>
<td>Suggestive but limited studies</td>
<td>Few studies identified this; more relevant to elderly samples</td>
<td>Positive findings: 43,144,198 Null/contrary findings:</td>
</tr>
<tr>
<td>Biomedical markers, blood pressure, cholesterol</td>
<td>These items were rarely included in generic models and were more often included in disease specific models</td>
<td>Moderate to strong</td>
<td>Limited evidence as a general predictor of admission, more relevant to disease specific models</td>
<td>Positive findings: 28,32,36,56,103,139,142 178,180–191,207–209,212,214 Null/contrary findings: 138, 163 for some markers e.g. blood pressure and blood glucose, serum albumin for some samples</td>
</tr>
</tbody>
</table>
### Lifestyle related risk factors

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Evidence Summarised</th>
<th>Measurement Issues</th>
<th>Positive Findings</th>
<th>Null/Contrary Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Smoking status</strong></td>
<td>Despite recent Australian population health evidence to indicate the importance of smoking status, studies concerning the risk for PPH/hospitalisation were limited and had equivocal findings. This may reflect measurement issues.</td>
<td>Measurement issues – some equivocal findings to date</td>
<td>Positive findings: 55, 56, 58, 80, 113, 148, 192</td>
<td>Null/Contrary findings: 92, 193, 194</td>
</tr>
<tr>
<td><strong>Alcohol consumption/ substance abuse</strong></td>
<td>Despite substantial population health evidence to indicate the importance of risky alcohol consumption in relation to disease, surveys and studies concerning the prediction of hospitalisation were limited and had equivocal findings. This may partly reflect some measurement issues.</td>
<td>Measurement issues – equivocal findings</td>
<td>Positive findings: 55, 56, 79, 192-194, 196</td>
<td>Null/Contrary findings: 58</td>
</tr>
<tr>
<td><strong>Physical inactivity/ activity</strong></td>
<td>There is substantial population health evidence to indicate the importance of adequate physical exercise, but relatively few studies that examined the level of physical activity in relation to the prediction of hospitalisation or readmission. Those that did indicated that greater physical activity was related to reduced PPH and readmission risk.</td>
<td>Moderate</td>
<td>Positive findings: 56, 58, 104, 147, 150, 154</td>
<td>Null/Contrary findings:</td>
</tr>
<tr>
<td><strong>BMI</strong></td>
<td>Despite substantial population health evidence to indicate obesity as a risk factor for various diseases, the findings in relation to hospitalisation were mixed. BMI is only rarely included in predictive risk models. Some studies and reviews identified low BMI as a risk factor.</td>
<td>Measurement issues – equivocal findings</td>
<td>Positive findings: 56, 203</td>
<td>Null/Contrary findings: 139</td>
</tr>
<tr>
<td><strong>Nutrition/ malnutrition</strong></td>
<td>A few studies indicated malnutrition was a risk factor for hospital admission, readmission, LOS and cost but some equivocal evidence41</td>
<td>Measurement issues – low BMI may be more relevant to elderly high-risk patients</td>
<td>Positive findings: 50, 56, 197, 198, 199</td>
<td>Null/Contrary findings: 58</td>
</tr>
</tbody>
</table>

---

41 Carpenter49 review article re elderly and ED suggests null findings
Comorbidity

Comorbidity for chronic disease and long-term conditions is associated with increasing costs for the health system, as the data from the Johns Hopkins ACG White Paper and Central Southern Commissioning Support Unit (CSCSU) below indicate. A large component of cost will include unplanned admissions, readmissions and LOS. With the ageing of the population, it is likely that the number of people with multiple chronic conditions is likely to increase. In the UK it is estimated that the number of people with three or more chronic conditions is expected to rise from 1.9 million to 2.9 million by 2018.

Figure 3: Relationship between the number of chronic conditions people have and average cost in the previous year

![Graph showing the relationship between chronic condition count and total cost](source)

Source: Johns Hopkins University (ACG)

Figure 4: Mean number of emergency unplanned admissions by number of chronic conditions

![Graph showing the mean number of emergency unplanned admissions](source)

Source: Central Southern Commissioning Support unit, NHS
Many predictive risk stratification models included a measure of comorbidity, and the majority of these studies indicated it is a significant predictor of hospital admissions and/or ED utilisation. A recent review by Wallace et al indicated that only 12 of 27 models to predict ED utilisation included comorbidity, which is surprising given the strength of evidence available. Other studies reported that comorbidity was a significant predictor of hospital admissions in the following year for community dwellers in Italy. Shah et al reported that a high comorbidity score was associated with a higher number of Medicare claims and that need (as assessed by comorbidity and health status) was the most significant and accurate predictor of ED use. O’Malley et al reported that people with COPD with a severe comorbid condition were twice as likely to be hospitalised. Brameld et al. indicated that people with more comorbidity and multi-morbidity had higher admission rates in Western Australia. The review by Muenchberger et al. indicated that for 18 out of 20 studies examined, comorbidity was significantly associated with avoidable hospitalisation. Katterl et al., from a review of four early studies, rated the evidence as strong for comorbidity as a predictor of potentially avoidable hospitalisation. However, they noted that earlier Australian studies showed that comorbidities made no significant contribution to rates of potentially avoidable hospitalisations, but state this may have partly been a function of poorly recorded data and coding errors that omitted comorbidities.

Comorbidity is also an important and widely investigated risk factor for the prediction of readmission and LOS, revealing that in general people with more comorbidity had higher readmission rates and longer hospital stay. Frigolla-Capell et al. found that comorbidities predicting readmission and long LOS were mostly chronic diseases. Another study, using a variant of the LACE+ index with a focus on comorbidities, showed significant predicting power for urgent readmission. Kansagara et al. found that almost all models they identified (24 out of 26) used comorbidity and disease specific information in their models with acceptable discriminating power. However, they also found that comorbidity was a better predictor of mortality than readmission. Hasan et al. reported that the Charlson Comorbidity Index appeared to be a significant predictor of readmission. According to Incalzi et al., the presence of more than three comorbidities is an important factor in predicting LOS.

The various studies have measured comorbidity in a variety of ways, including the Charlson index and variants, crude counts of the number of chronic diseases or diagnoses, or by using group classifications (e.g. clinical risk groups or Hierarchical Condition Categories or clusters) which are often based on comorbidity. Sharabiani et al. undertook a systematic review of comorbidity indices in relation to the prediction of mortality and found the Deyo variant of the Charlson index was the most commonly referred to index, followed by the Elixhauser measure. They noted that comorbidity adjustment methods seem to better predict long-term mortality than short-term mortality, and the Elixhauser measure seemed to be the best predictor for this outcome. A similar review of comorbidity methods for the prediction of hospitalisation is required. Harrison et al. examined different measures of multi-morbidity using a large, prospective, cross-sectional study in Australian general practice, and they raise a number of issues concerning the accuracy of measuring comorbidity using different methods. They define ‘complex multi-morbidity’ as the occurrence of three or more chronic conditions affecting three or more different body systems within one person without defining an index chronic condition. They suggested this may be useful in identifying high-need individuals and could be considered for comorbidity measurement in risk stratification models.

Population health research has also identified important comorbidity factors and clusters that related to hospitalisation risk. A large nationally representative random sample of those over 65 years found that
people with three chronic conditions were 37 times more likely to be hospitalised, and those with four conditions or more had 99 times the risk of hospitalisation. Niefeld et al.\textsuperscript{138} reported that comorbidities among people over 65 years with type 2 diabetes increased the likelihood of avoidable admissions. AIHW\textsuperscript{81} noted that the cluster of CVD, diabetes and CKD was associated with 20% of all hospitalisations in Australia in 2012–2013, and comorbidity between these diseases was high. Risk factors such as smoking, high blood pressure, overweight and obesity, physical inactivity and unhealthy diet are also associated with these conditions, and a report on this aspect is due in 2015.

\textbf{Presence of particular diagnoses}

Damush et al.\textsuperscript{139} indicated that the presence of a diagnosis of diabetes, CHF, or anaemia was a risk factor for hospitalisation for the elderly or those over 50 years with a chronic disease. Frigola-Capell et al.\textsuperscript{120} examined risk factors for hospitalisation, readmission and LOS for ambulatory patients with heart failure and found that additional diagnoses of CKD, IHD, diabetes and COPD substantially increased risk for these outcomes. Kansagara et al.\textsuperscript{68} noted that the presence of mental health comorbidities or mental illness was included in nine models used to predict readmission, and mental illness was mentioned as a significant factor by a number of studies\textsuperscript{11,111} and raised as an issue for predicting readmissions in review articles.\textsuperscript{19,21,140} Philbin and Di Salvo\textsuperscript{141} and Krumholz et al.\textsuperscript{142} reported a history of diabetes as an important predictor of readmission in their models. Kirby et al.\textsuperscript{143} found that frequently readmitted patients were more likely to have diagnoses of mental illness, COPD, dyspnoea or chronic heart failure. Amarasingham et al.\textsuperscript{77} found a history of depression or anxiety were significant predictors of readmission.

The Emergency Admission Risk Likelihood Index (EARLI)\textsuperscript{43}, used for screening of the elderly in the community, includes the presence of heart problems as a significant predictive factor. A similar screening tool, the Probability of Repeated Admission (Pra) score, includes the presence of diabetes and IHD.\textsuperscript{42,144}

\textbf{Severity of illness or condition}

Many of the broader and generic predictive risk stratification models are based on a casemix-style clinical group classification associated with severity (e.g. adjusted clinical groups\textsuperscript{10}, Hierarchical Condition Categories\textsuperscript{53,121}) or include a variable of this kind in the model which serves as a proxy for case complexity or severity, and which may also be used for risk adjustment purposes. Specific disease severity factors and indicators are more likely to be included in disease specific models.

Damush et al.\textsuperscript{139} included a crude ‘groups’ measure severity of disease in their model but found that the presence of particular diseases (diabetes, CHF and anaemia) were more significant predictors. Louis et al.\textsuperscript{30} found that chronic diseases were prevalent in high-risk patients, as were mental health problems. For those hospitalised in previous years (period five years), specific severity stages of certain chronic diseases (coronary artery disease, diabetes) were predictive of future risk.

Ansari\textsuperscript{19} notes that severity of illness is an important factor in explaining variations between areas and populations, and it is necessary to adjust for this in order to correctly quantify barriers to primary care access or quality of primary issues in the community. O’Malley et al.\textsuperscript{29} found that prior hospitalisation for the same condition (COPD and pneumonia) and having more comorbid conditions in the baseline year were strongly associated with higher risk of hospitalisation during the follow-up year. They also noted the importance of adjusting for patient SES and baseline health in any attempt to use ACSC hospitalisations as
an indicator of quality. The Muenchberger et al. review identified that 13 of 14 studies that included a variable related to severity of illness/condition showed this was an important predictor of risk for avoidable hospitalisation – although it was unclear which studies were examined. Katterl et al. found that severity of disease was associated with PPH. Louis et al. tested a predictive model which showed that in patients hospitalised in previous years, specific severity stages of certain chronic diseases, such as coronary artery disease and diabetes, were predictive of future risk.

Several studies examined the role of severity of illness in predicting readmission and LOS in hospital. Garcia-Perez et al. in their review listed illness severity as a significant predictor of hospital readmission in the three months after discharge in elderly patients. They also mentioned that in two of the studies they reviewed, patients who stayed longer in hospital in previous admissions showed increased risk of readmission, and one of the reasons could be severity of the illness. Kansagara et al. in their review of 26 models found that only one included an index of illness severity in predicting readmission, although others included laboratory test and biomedical markers. Hughes et al. developed a model using clinical risk groups based on levels of severity of illness to predict future use of health care resources. However, there was no explicit mention of readmission or LOS.

It is comprehensible from the above description that disease severity is a significant predictive factor for future health care utilisation. However, there were relatively few studies focusing on specific issues such as repeated admission or LOS.

**Self-rated health**

Muenchberger et al. noted that there were 27 prior studies which identified the importance of health status (physical, mental) and/or health-related quality of life (HRQOL) as predictors of preventable hospitalisation, but only a small proportion of these studies were actually discussed. Poor scores on these measures (e.g. health status, HRQOL measures, disease specific symptom scores) were associated with a higher risk of avoidable hospitalisation.

Diette et al. found that lower self-reported health status and more asthma symptoms were univariate factors that were significantly associated with ED hospitalisation in the follow-up year, and asthma symptom index scores remained significant in the multivariate model. Parkerson et al. classified primary care patients by their age, gender and scores on the Duke Health Profile to form four classes for risk of hospitalisation in the following year. Comparisons were made with models that used diagnoses or severity of illness as predictors. The positive likelihood ratio for predicting highest risk for primary care visits was 2.2 for the HRQOL model compared with 1.8 for the diagnoses model, 1.6 for the severity model, and 1.5 for age and gender alone. One-year actual primary care visits and charges increased step-wise from the lowest to the highest risk class. Although the highest-risk patients represented only 18.6% of the test group, they accounted for 26.7% of the primary care clinic visits, 31.6% of the clinic charges, 34.6% of the hospital days, 35.1% of hospital charges, and 30.8% of total charges at all health care sites. Although there were significant risk class differences for primary care utilisation, there was no difference for high-risk patients concerning the use of subspecialty clinics or emergency room visits.

The EARLI43 model included a self-rated health item in the final predictive model, and this has as adequate discriminative capacity and positive predictive value as many more sophisticated predictive models. A similar tool, the Pra score, also included a self-rated health item and has a similar level of ‘pooled’
predictive performance. A risk stratification associated intervention study by Counsell et al.\textsuperscript{152} included a self-rated health measure and found there was evidence for an improvement in the mental health status domains (mental, social, vitality) but not for the physical health status domains.

The Schatz et al.\textsuperscript{153} baseline survey of asthma patients included validated measures of generic health status, asthma specific quality of life, asthma control and asthma symptom severity. Relationship of survey variables with subsequent utilisation was assessed and patients with higher scale-defined morbidity were as much as four times more likely to have subsequent ED utilisation (sensitivity as high as 58\%; specificity as high as 78 per cent). However, while addition of an asthma specific tool to either demographic or utilisation prediction models added sensitivity (as much as 15\%), it did not substantially improve the overall prediction properties of models containing both demographic and utilisation predictors. Sprenkle et al.\textsuperscript{151} reported that survey scores on the physical component summary scale of SF-36\textsubscript{V} were an independent predictor of hospitalisation and outpatient utilisation in the following year. Those with poorer self-rated health were almost twice as likely to be admitted to hospital. Two other studies found that poor self-reported health status was a predictor of hospitalisation and ED utilisation.\textsuperscript{110,124}

Studies concerning readmission\textsuperscript{110,147,150} indicated that worse physical and mental health status and activity scores were significant factors associated with rehospitalisation. Garcia-Aymerich et al.\textsuperscript{154} examined readmissions for COPD and found that higher levels of usual physical activity were associated with a reduced risk for readmission (HR=0.54). Gudmundsson et al.\textsuperscript{149} found a significant increase in rehospitalisation risk associated with scores on asthma impact and activity scales and quality of life scales, but no association was found for the asthma symptom scale. A study by Costa et al.\textsuperscript{111} assessed patients with the interRAI Contact Assessment tool (a tool to assess the performance and capacity of a patient as well as the presence of symptoms and conditions) at an ED visit and found that poor self-reported health was one of the significant factors that best described those at risk of long LOS (AUC=0.70). Szekely et al.\textsuperscript{155} assessed the self-rated health status of patients prior to a CABG procedure and examined in-hospital mortality and long LOS. They found that, after adjustment for regional differences, mental composite score (MCS) and physical composite score (PCS) were associated with prolonged hospital stay.

Hasan et al.\textsuperscript{102} reported that the SF-12 physical component score was a significant predictor in their early readmission risk model, but this model overall had a relatively poor discriminative performance. Kansagara et al.\textsuperscript{68} indicated that three readmission prediction models have included variables relating to self-rated health and quality of life in their final model.

Overall, there seems to be a moderate to strong effect for these variables in relation to health service utilisation, but one may suspect that the sensitivity of some of the instruments used to detect differences between groups might also play a role in these findings.

Functional status, disability and cognitive impairment

Wallace et al.\textsuperscript{69} reviewed risk prediction models to predict emergency admission in community dwelling adults and indicated that very few models included such factors as functional status or falls. QAdmissions\textsuperscript{65} and the Devon Predictive Model\textsuperscript{39} have included falls as a significant predictive factor. ACI\textsuperscript{2} indicates that falls are a common reason for ambulance transport to ED and the number of falls in the past 12 months has been included in ACAT assessments\textsuperscript{156}, so it would seem worthwhile to include. Visvanathan et al.\textsuperscript{126} noted that non-well-nourished users of domiciliary care services reported more falls and were more likely to be
admitted to hospital, and West et al. noted an association between hospital admissions related to falls and social deprivation for those over 75 years. Some models that are based on, or include, self-report surveys (e.g. Lyon et al.) have included mobility independence items. Damush et al. included physical function in their predictive model and found that better physical function was inversely associated with non-elective admission. The absence of Activities of Daily Living (ADL) dependency was found to reduce the risk of one-year mortality and nursing home placement among older ED patients. Panattoni et al. noted that variables such as function have been shown to add some predictive power in a small number of models.

Aspects of function are more likely to be assessed in the research concerning readmissions and LOS. Aminzadeh et al. found in their systematic review that ED stay was associated with unmet functional needs along with four other risk factors. Similarly, a predictive role of functional status for early readmission and impaired locomotion and age-related physical functional status for LOS has been reported. Garcia-Perez et al. found that in patients over 75 years, functional disability was a significant predictor of readmission in some studies but not in other studies. In a Spanish study, Loren-Guerrero et al. found that cognitive impairment and physical dependence were significantly associated with LOS. Hebert et al. claimed there was a higher risk of rehospitalisation among the PRISMA control group, although there was no mention of statistical significance. Iloabuchi et al. in their study of early readmission among low income elders found that functional or activity limitation (as indicated by receiving new assistive device in the past six months) was significantly associated (OR=2.26) with readmission. Dependency for daily activities (ADL and IADL) was found to be predictive of inappropriate hospital use days. Curry et al. reported an increase of predictive power of some models after using health status and functional impairment data.

A review by Covinsky et al. states that re-engineered hospital care that focuses on function (including assessment on admission and throughout the hospital stay, promoting physical activity, avoiding hospital processes and complications that impair functional recovery such as too much bed rest) and planning for discharge home with the support needed to complement a patient’s functional capacity may reduce the incidence of hospitalisation associated disability. These factors could also potentially be related to hospital readmissions.

However, Carpenter et al. found in their review that individual factors such as dependency independently did not increase the likelihood of adverse outcomes, including ED returns and readmission for the elderly. Similarly, in another study, Incalzi et al. found that physical and mental function were not predictive of LOS among COPD patients.

There are some studies that evaluate simple rating scales/triage tools to predict readmissions. Graf et al. found that the use of tools such as ISAR (Identification of Seniors At Risk) and TRST (Triage Risk Screening Tool) modestly predicted unplanned readmission (AUC=0.60–0.66). Meldon et al., studying the TRST, found that walking difficulty emerged as a significant predictor of ED revisit within 30 days in elderly patients.

Related to the assessment of function is the assessment of frailty. The NHS noted the need for the increased identification of frailty in the absence of multi-morbidity, as apparently frail elderly people without comorbidity are not well identified by the parameters of current risk stratification tools used in the UK. About one-third of elderly people in the UK have only one long-term condition. Three easy to use examples of screening tools for frailty included the Walking Speed Test, the PRISMA 7 Questionnaire (used in Canada for initial risk screening and a system-based electronic tool. Even the global self-rated health item was
reported as having adequate sensitivity and specificity as a crude screening measure. Although sensitivity and sensitivity data for these measures were reported, further assessment of their psychometric and predictive properties may be required.

Daniels et al.163 assessed community dwelling elders using three tools concerning frailty (Groningen Frailty Indicator, Tilburg Frailty Indicator and Sherbrooke Postal Questionnaire) and examined hospital utilisation in the following year. All instruments showed significant differences by frailty group and higher risk odds for the very frail group, but the AUC statistics for the models were all below 0.64 for mortality and below 0.60 for hospitalisation. The positive predictive values were also very low, indicating poor predictive performance. Forti et al.164 examined indicators of the physical frailty phenotype (weight loss, inability to rise five times from a chair, exhaustion) and cognitive impairment and serum albumin levels for elderly admitted patients in relation to LOS and unfavourable discharge outcomes. All these predictors, both alone or in combination, had poor discriminatory ability (AUCs<0.70) and were of limited clinical usefulness, and thus the authors concluded that these markers of frailty had limited applicability for risk stratification. Similar findings concerning frailty risk assessment tools (ISAR, TRST, Variable Indicative of Placement risk) were reported by Carpenter et al.49. O’Caiomh et al118 reported on the development of the RISC (Risk Instrument for Screening in the Community) frailty assessment tool, but this tool needs to be validated and evaluated in a prospective study and currently has limited psychometric evidence to support its use.

Falasca et al.40 applied MoSaiCo, a modified Combined Predictive Model (CPM), to the Ravenna population (18+ years) to predict the risk of a binary variable of ED admission and mortality (EAM). This model included some additional factors such as invalid/disability status and living alone over 75 years, and included use of home care, social services and mental health services, and prescription data (polypharmacy). They identified ten EAM risk categories for those over 75 years and found use of social services, invalid status, becoming non-self-sufficient during follow-up, two or more chronic diseases and multiple prescriptions monotonically increased with increasing EAM risk category. The authors suggested that these scores could potentially be used to predict frailty from a population screening base, although the definition of frailty used here is very broad compared to the ‘readmission’ tools above. It is, however, similar to self-report screening models outlined by Boult et al.144 and Lyon et al.43

Falasca et al.40 undertook one of the few studies to include invalid status or long-term disability in a model, although Gao et al.27 also found that disability status was a significant predictor of potentially avoidable hospitalisation in a sample of veterans. National Disability Services165 noted that people with a disability who are service users of Ageing, Disability and Home Care have a rate of hospitalisation that is significantly higher than the rest of the NSW population, particularly for those aged over 65 years. Based on the findings of this report and those of Russell et al.166, ACI2 identified that “the multiple and often inadequately understood care needs of the disabled during or in the lead-up to hospitalisation result in a high likelihood for poorly coordinated and responsive care, and rapid discharge planning. Many times, this can result in readmission.”

Other areas of impairment that are less often considered include the presence of cognitive impairment. Carpenter et al.49 suggest the inclusion of dementia status in tools to assess risk of frailty. The EARLI model (which is based on self-report data from primary care) includes memory/confusion problems.43 Wallace et al.69 identified that 7 out of 27 models used to predict ED admissions include a measure of cognitive impairment. However, a model by Damush et al.139 based on secondary analysis of RCT data actually excluded people with impaired cognitive status.
Beuchet et al. screened elderly patients in the ED in order to predict LOS, and this included the assessment of cognitive status. Although the sample was small, a classification tree algorithm suggested interactions between variables in predicting long LOS (e.g., a history of falls, male gender with cognitive impairment). Guerrero et al. reported that cognitive impairment was the most significant predictor of LOS in a tertiary acute care hospital. Belleli et al. examined 12-month outcomes post-discharge from a rehabilitation unit and found that cognitive status was significantly associated with institutionalisation outcomes, and that comorbidity and delirium during the 12-month follow-up period were independent predictors of rehospitalisation. Kansagara et al. noted that 12 predictive models for readmission examined cognitive status variables, but only seven included cognitive status in the final model.

**Medication use**

Most of the previous review articles indicate that polypharmacy or the use of three or more medicines is a strong risk factor for hospital admissions, and a number of the predictive risk models for hospital admission and ED attendance include prescription data and identify medication use as an important risk factor. Some studies also indicated higher risk associated with particular prescription use (e.g., antidepressants, antibiotics, antipsychotics, analgesics, diuretics, respiratory medications), and Louis et al. also identified inappropriate prescriptions as a risk factor for hospitalisation. The Clinical Epidemiology and Health Service Evaluation Unit (CEHSEU) noted that the incidence of preventable adverse drug event admissions ranged from 2.4% to 3.6% of admissions, with higher rates of up to 22% for older patients.

The study on Drug Burden Index found that higher scores on this index independently predicted LOS (HR=1.23). Curry et al. reported an increase of predictive power of some models after using pharmacy data regarding medication, as do Parker et al. Similar predictive ability of number of medications was reported for LOS. Incalzi et al. reported that use of more than three drugs (OR=1.29) and use of respiratory depressant drugs (OR=1.24) prior to admission were significant predictors of LOS. The study of the TRST tool showed medication use was a significant predictor of ED revisits within 30 days. Betihavas et al. studying rehospitalisation among CHF patients, reported that appropriate use of medication was associated with risk reduction. However, though unexpected, a study by Pugh et al. showed that high-risk medication had no role in predicting readmission. Taha et al. tested a model based on a simple seven point readmission risk score which included polypharmacy (10+), and this was found to be significantly predictive of hospital readmission.

A related issue is non-adherence to prescription advice, and this has been associated with higher rates of hospitalisation in a few studies. A study by Wamala et al. indicated that inability to afford prescribed medicines was associated with non-adherence. Further studies are required to examine this aspect.

**Biomedical markers**

Muenchberger et al. noted that in the earlier literature, biomedical markers were frequent and significant predictors of hospitalisation for chronic disease. They reported that 17 of 19 earlier studies had significant findings, although it was difficult to identify which studies were included in this analysis. Most biomedical markers were condition specific, such as Forced Expiry Volume (FEV) for asthma, and common markers
studied include FEV, breathlessness, hypertension, BMI (both low and high), blood pressure (systolic) and HbA1c level.

AIHW\textsuperscript{56} examined high blood pressure, which is a prolonged elevation of the blood pressure that may cause the heart to work harder than normal, causing it to enlarge and weaken over time. The causes of high blood pressure are similar to other CVDs: poor diet (particularly high salt intake), obesity, excessive alcohol consumption and insufficient physical activity. Based on self-reported data from the 2007–08 National Health Survey, 12% of Australians reported having high blood pressure. Only a few risk stratification models included high blood pressure (e.g. Billings et al.\textsuperscript{36}, Chin and Goldman\textsuperscript{103} and Damush et al.\textsuperscript{139}).

Damush et al.\textsuperscript{139}, with a sample of frail elderly people, included laboratory test data in their model and reported that non-elective hospital admission was associated with lower BMI, lower haemoglobin levels, lower albumin levels, and higher serum creatinine and potassium levels. Blood pressure (systolic and diastolic) and blood glucose were not significant in this model. Inouye et al.\textsuperscript{28} found that abnormal laboratory test results (haematocrit, serum albumin, serum creatinine or any abnormal laboratory result) were predictive of hospitalisation in their development sample on elderly community dwelling people, but they did not include them in their final predictive model.

With regard to the disease specific literature, Betihavas et al.\textsuperscript{48} reviewed six risk stratification models for predicting readmission for chronic heart failure. They indicated that blood urea nitrogen was a significant predictor of readmission in more than one model.\textsuperscript{176,177} Saltzman et al.\textsuperscript{178} included serum albumin level, blood clotting, International Normalised Ratio (INR) and systolic blood pressure in developing a risk stratification measure for acute upper gastrointestinal bleeding, and found these factors were significant predictors of LOS and cost. Smith et al.\textsuperscript{32} provided a model for risk stratification for heart failure. The final model tested in one large US health plan included age, cardiovascular stays in the previous year, systolic blood pressure, renal function, ejection fraction/severity proxy, posterior wall thickness on echocardiogram, atrial fibrillation, coronary artery disease, chronic lung disease, hyperlipidaemia and stroke as significant predictors for hospitalisation.

With regard to high blood cholesterol, AIHW\textsuperscript{56} indicate that self-report data for this variable from population surveys is unreliable and few studies or risk models included this variable. In several studies and reviews, clinical, biochemical and haemodynamic parameters are examined, along with other patient- and physician-related factors responsible for readmission in health failure patients.\textsuperscript{179} These studies revealed that certain serum biomarkers, such as biochemical indicators of worsening renal function during hospitalisation\textsuperscript{180,181}, decreased renal function at admission\textsuperscript{182,183}, elevated blood urea nitrogen\textsuperscript{184,185}, persistent hyponatraemia\textsuperscript{186}, anaemia\textsuperscript{187}, elevated pre-discharge B-type natriuretic peptide\textsuperscript{188,191}, elevated cardiac troponin T and elevated cystatin levels\textsuperscript{190}, were important predictors of readmission in heart failure patients.

Some of these biomarkers are clearly significant for admissions for specific diseases and are more likely to be included in disease specific stratification models. However, some are so specific to the particular condition/disease that they would not be particularly relevant to include in generic and whole of population risk stratification approaches.
Population health-related risk factors

Some risk factors, such as current smoking status, risky alcohol use, physical inactivity, nutrition, BMI, overweight or underweight, high blood pressure and high blood cholesterol, are often included in population surveys as they are associated with risk for hospitalisation. Some of the predictive risk models (e.g. Billings, Hippisley-Cox) include some of these variables and they can also be included in the ACG models. Some research studies also examine these factors in relation to health service utilisation, including hospitalisation.

AIHW examined risk factors associated with chronic disease. Health/clinical factors included insufficient consumption of fruit, vegetables and whole milk; physical inactivity; risky alcohol consumption; daily smoking; obesity; and high blood pressure. As people reported more risk factors, they were more likely to have a chronic disease (e.g. females with five or more risk factors were three times more likely to report stroke etc.). They noted that some combinations of risk factors are more common than others (e.g. daily smoking and risky drinking, daily smoking and physical inactivity), which have the capacity to amplify the potential health effects. Although it is useful to examine population risk factor rates for chronic disease in planning preventive interventions, to include such factors in predictive risk factor models for hospital admission may be dependent on the prevalence of these risk factors in the targeted populations (e.g. 65+) and their predictive value for hospitalisation outcomes. For example, many people with chronic or long-term conditions (excluding asthma) are over 65, and the rates of smoking and risky drinking are much lower for these elderly age bands. For elderly groups, current smoking and alcohol consumption status may be low, but there may have been a prior history of risky alcohol use which raises issues about the measurement of such variables. Models that targeted the elderly did not appear to include such factors, but they may be more relevant to include in models that take a whole of population approach.

Tran et al. examined some of these risk factors with regard to the multi-variable adjusted hazard ratios for PPH. Non-smoking was significantly associated with a reduced risk of PPH (HR=0.74) as was more than two and a half hours per week of exercise (HR=0.74). There was little difference in the risk for those eating a healthy diet (HR=0.99), but relatively few within the sample (23.5%) ate two or more servings of fruit and five or more servings of vegetables per day. Conversely, lower alcohol consumption was associated with an increased risk for hospitalisation (HR=1.15), but it was noted that alcohol consumption in relation to PPH has a J-shaped curve. AIHW provide the hospitalisation rates for CVD, CKD, diabetes and stroke, and note that risk factors such as smoking, high blood pressure, overweight and obesity, physical inactivity and unhealthy diet are associated with these conditions. A report on this aspect is due in 2015.

Smoking status

There is evidence that current and previous smoking status is a risk factor for many diseases and conditions which, in turn, will affect the PPH rates for such diseases. AIHW also noted that daily smoking rates are associated with a gradient of social disadvantage and distance from major cities (rurality). Tran et al. examined non-smoking status with regard to the multi-variable adjusted hazard ratios for PPH. Non-smoking was significantly associated with a reduced risk of PPH (HR=0.74).

As mentioned earlier, relatively few of the predictive risk models actually included smoking status. Godtfredsen et al. found that cessation of smoking halved the risk of hospital admission for COPD patients, but a reduction in smoking did not significantly reduce the risk for hospitalisation. Morris et al. reported that smoking was among a cluster of factors (mainly variables associated with social deprivation)
that were associated with elevated hospitalisation rates for respiratory conditions. Evangelista et al.\textsuperscript{192} found that CHF patients who continued to smoke were twice as likely to have multiple readmissions. However, there are studies\textsuperscript{92,193,194} that found no association between smoking status and hospitalisation risk, even though two of these studies also concerned respiratory conditions.

**Alcohol consumption**

AIHW\textsuperscript{56} notes that regular alcohol consumption at high levels can contribute to the development of chronic conditions such as liver disease, some cancers, oral health problems and CVD. The reduction of consumption can reduce the risk for these conditions. Alcohol consumption can also contribute to excess body weight. When assessed by risk level, 15\% of males and 12\% of females consumed alcohol at levels considered to be risky for their future health. Recent research\textsuperscript{155} has indicated that risky alcohol consumption causes 15 deaths and 430 hospitalisations in Australia each day. Tran et al.\textsuperscript{58} found that lower alcohol consumption was associated with an increased risk for hospitalisation (HR=1.15), but it was noted that alcohol consumption in relation to PPH has a J-shaped curve. Within the less than 14 alcoholic drinks group, there is a cluster of cases that report no alcohol consumption and it might be that this group may include people who no longer consume alcohol for health reasons.

Whole of population risk stratification models sometimes include alcohol consumption as a risk factor\textsuperscript{36,65} for hospitalisation, but many do not. As indicated by Tran et al.\textsuperscript{58}, the association between alcohol and PPH does not appear to be linear. An early study by Billings et al.\textsuperscript{196} in New York City found that 11.6\% of ACSC admissions had alcohol or substance abuse as a secondary diagnosis, and there was variation by disease and SES. An article by Charalambous et al.\textsuperscript{114} discusses the use of a screening tool for alcohol misuse (e.g. AUDIT tool) to refer relevant ED presentations to alcohol health workers or services in order to reduce the number of alcohol-related presentations to the ED. They cited a study by Wright et al.\textsuperscript{117} using such a program and noted a reduction in hazardous drinking for such cases, but no data concerning the reduction in ED presentations or admissions was presented. Raven et al.\textsuperscript{79} undertook interviews of high-risk patients in a Medicaid cohort that were actually admitted to hospital during the one-year follow-up period, and for 42\% of these patients the admission was associated with substance abuse.

Kansagara et al.\textsuperscript{68} also indicated that alcohol consumption was not included, evaluated or even considered in readmission models, although Amarasingham et al.\textsuperscript{77} included a history of cocaine use in an electronic readmission model. Evangelista et al.\textsuperscript{192} found that CHF patients who continued to use alcohol were five times as likely to have multiple readmissions.

Further information on alcohol consumption as a predictor of potentially avoidable hospital admission is required. Given the variable’s distribution issues noted by Tran et al.\textsuperscript{58}, further consideration needs to be given to the best way to measure this factor, and also whether it is better to focus on current consumption or a history of risky drinking. Although some models have included alcohol consumption as a predictor, they have not yet produced papers or reports that address this particular issue.

**Physical inactivity**

AIHW\textsuperscript{56} indicated that being physically active (assessed as having two and a half hours of exercise in five sessions over one week) can help prevent or minimise the risks of CVD, type 2 diabetes, some cancers and osteoporosis. It can also help in the management of biomedical risk factors, such as body weight, high blood pressure and high cholesterol. AIHW\textsuperscript{56} report that in 2007–2008, 59\% of those surveyed did not undertake sufficient physical activity to confer a health benefit. Tran et al.\textsuperscript{58} found that having sufficient
physical activity reduced the multivariable adjusted risk of PPH (HR=0.74). They also found that sitting for less than eight hours per day reduced the risk of PPH (HR=0.86). Studies by Emtner et al. and Pitta et al. have indicated that physical activity factors are related to risk of readmission to hospital. Garcia-Aymerich et al. examined readmissions for COPD and found that higher levels of usual physical activity were associated with a reduced risk for readmission (HR=0.54). Most predictive models do not include indicators of physical activity or inactivity, but some include indicators of mobility.

**Nutrition**

Population-based surveys have examined healthy diet factors such as the daily consumption of fruit and vegetables. Tran et al. found there was little difference in the risk of PPH for those eating a healthy diet (HR=0.99), but relatively few within this sample (23.5%) ate two or more servings of fruit and five or more servings of vegetables per day.

Baumeister et al. assessed the nutritional status (Geriatric Nutritional Risk Index) of community dwelling elders at baseline using interview and blood test data (for biomedical markers). These patients were followed up over a 10-year period. They reported that participants with lower nutritional status had 47% higher costs and a 50% higher risk of hospitalisation at follow-up than those persons with adequate nutritional status. Visvanathan et al. assessed elders using domiciliary care services for their nutritional status and found those that were not well nourished were more likely to be admitted to hospital (RR=1.51), have two or more admissions to the ED in the follow-up year (RR=2.96), and were more likely to spend four weeks in hospital during this year (RR=3.22). However, the data did not appear to be adjusted for potential confounders.

Allen et al. reported that malnutrition was a significant predictor of LOS for inpatients with systolic heart failure. Guerra et al. assessed the nutritional status of inpatients and found that high and severe undernutrition was a predictor of total hospital cost. Carpenter et al. reviewed studies that concerned the risk of adverse outcomes for elderly ED admitted patients (ED return, hospitalisation). They found that poor nutrition (as assessed by the Mini Nutritional Assessment Short Form) was not a significant risk factor for adverse outcomes.

While malnutrition appears to be an important risk factor, the evidence is equivocal and further research is required.

**Body Mass Index**

AIHW reports that in 2007–08, only a small proportion of people (less than 3%) aged 15 and over were classified as underweight. A further 38% were classified as normal weight and 60% were classified as either overweight or obese. Korda et al. found a dose-response relationship between above normal BMI and hospital costs, admissions and bed days when compared with normal BMI, but they did not examine those with low BMI. Only a few whole of population models included BMI (e.g. Billings et al.) and the Wallace et al. review indicated that this factor is not included in most predictive risk modelling tools. Similarly, Kansagara et al. indicated that this issue was not addressed in readmission risk tools. However, being underweight was identified as a risk factor for hospitalisation and/or readmission by two studies, and two reviews noted that despite obesity being recognised as a major risk factor for CVD and diabetes, there was some evidence for the ‘obesity paradox’ – namely, that a higher BMI may be associated with a lower mortality and better outcome in several chronic diseases for elderly persons.
Some models and research studies included the presence of leg ulcers as a significant predictive factor for hospitalisation or LOS.43,145,198 A review by Carpenter et al.49 of 12 studies suggested pressure sore risk did not predict adverse outcomes for undifferentiated ED patients, although only one study actually addressed this risk factor.

4.3 Prior utilisation factors

Prior utilisation variables such as ED visits, ED admissions, ACSC admissions, non-elective hospital admissions and hospital admission (undifferentiated) are commonly used in nearly all risk stratification models to predict hospital admissions. Wallace et al.69 noted that 22 out of 27 models that were used to predict ED hospital admission used prior emergency hospital admission data as a key and significant predictor. Fourteen models collected data on prior ED/ER visits, 13 models collected data on prior outpatient department visits, 8 models included prior GP visits, and 5 models collected data on previous bed days. Gao et al.27 examined four models which successively included hospital characteristics, patient demographic and socio-economic variables, prior utilisation and costs data, and Hierarchical Condition Categories (comorbidities). Adding prior utilisation and cost data increased the predictive power by an additional 11 per cent. Three models also included prior elective admissions, but only three models collected data concerning prior ACSC admission.

Billings et al.36 tested four models incorporating a variety of prior service utilisation variables. The study noted that inclusion of A&E data improved the predictive value and identified more high-risk patients at little cost. Adding outpatient data marginally improved case identification but at a small loss of positive predictive value, and the model including GP data had the most predictive power. The collection of GP data presented challenges for access, data linkage and for improving data quality, but the improved case finding suggested that overcoming these barriers would be worthwhile.

Donnan et al.37 tested an algorithm for predicting ED hospitalisation in which the number of previous admissions and prior total bed days appeared to be strong predictors. Enard et al.203, in an intervention trial involving patient navigation, showed that for intervention patients with lower prior ED utilisation, there was a significant reduction in ED visits for the first year but not for the second year. The intervention did not have any effect on very frequent ED visitors (three or more visits in the prior two years).

Garcia-Perez et al.129 in their review of predictors of readmission found significant association with prior hospital utilisation and a longer length of index hospital stay. In the study examining 26 models concerning prediction of risk of readmission, Kansagara et al.68 mentioned that most models included variables for use of prior medical services. Lemke et al.204 examined an acute care hospitalisation model using the ACG system with added prior hospital utilisation variables. They found a readmission rate of 20% among the patients who had been hospitalised during the previous year. The prior utilisation model had a good discrimination power (AUC=0.75). In another study testing the TRST tool, prior ED use was identified as a significant predictor of ED revisit within 30 days by elderly patients.130 A risk prediction model designed to study the effect of frailty-related diagnoses, high-risk medications and primary care visits in the prior year in the elderly on early readmission (<30 days) showed that prior hospitalisation (OR=1.24) was significantly associated with readmission.173 Taha et al.174 in their study of readmission risk prediction used a seven point scoring system which included hospitalisation in the previous six months. The study showed that higher scores were a significant predictor of readmission. Van Walraven et al.53 studied the LACE+ index which
consists of LOS of index admission (L), acuity of the admission (A), Charlson Comorbidity Index (C) and ED visits in the six months prior to index admission (E). The index was found to have moderate discriminating power. In another study, along with another four variables, previous admission was found to be significantly associated with prediction of readmission.

Although there is substantial evidence that prior hospitalisation is a significant predictor of future hospitalisation, there is a need to remember that there is also evidence that those who are hospitalised more often in one year and identified as ‘high risk’ may not be such high users in following years due to regression to the mean effects. Stratification models using an index admission are likely to be prone to such effects. This also emphasises the need for a control group when studying the effects of targeted integrated care interventions.

As indicated above, relatively few models include primary care utilisation data as predictors of hospitalisation. Wallace et al. noted that eight models included prior primary care visits, and in the Inouye et al. model, six or more primary care visits in the previous year was one of five predictive factors included. A report by ACI referring to the recent APHID study indicated that prior high primary care service utilisation appeared to be associated with the likelihood of hospitalisation. Some of the studies indicated that continuity of primary care was an important factor (e.g. Chenore et al., Mian et al.) that was related to a lower risk of hospital admissions. The lack of availability of, or access to, primary care services has been raised by a number of authors as a factor associated with an increase in ED admissions.
5 Social and clinical risk factor summary

The review of socio-demographic and social risk factors indicated that age, gender, a broad measure of social disadvantage, rurality and Aboriginal and Torres Strait Islander status had good evidence to support their inclusion as predictors in a risk stratification system for NSW (see Table 2). Gender will be needed for risk adjustment if comparison across districts is required, but interactions between gender, age and disease in relation to hospital admissions have been noted. There was also reasonable evidence to support the inclusion of an indicator concerning social support. It is noted that ‘living alone’ is only a proxy variable for social support as it does not measure social support directly. However, a comprehensive measure of social support, such as that used by Rodriguez-Artalejo et al. would only be possible to use in models that use self-report data or that combine self-report data with administrative data or in research studies. In the first instance, it is thought a variable such as ‘living alone’ could be trialled as it would be difficult to routinely include detailed social support data either in self-report or administrative datasets; however, the limitations of this proxy variable are acknowledged (see page 11). Although living alone was found to be a significant predictor of hospital admission in a number of studies, it does not necessarily imply that all those that live alone will be lacking in social support.

With regard to clinical risk factors (see Table 3), comorbidity or multi-comorbidity had substantial evidence to support its inclusion in any model. Some consideration may be given to the best method to assess comorbidity or multi-morbidity. Severity of condition or illness was not so routinely or directly addressed in either predictive risk models or in other research literature, although many of the leading models for predicting hospital admission include a casemix style clinical group classification associated with severity (e.g. adjusted clinical groups, Hierarchical Condition Categories, Hughes et al.), or a variable of this kind in the model which serves as a proxy for severity. Ansari and O’Malley et al. note that severity of illness is an important factor in explaining variations between areas and populations, and it is necessary to adjust for this in order to correctly quantify barriers to primary care access or quality of primary issues in the community. Fewer of the readmission prediction models included a measure of severity of illness, but disease specific models tended to include more symptom indicators related to severity of illness/condition.

Particular diagnoses such as heart problems, anaemia, CHF, IHD, diabetes and coronary heart disease were included in some models, especially self-report models (e.g. Pra model, EARLI model), but most models based on administrative data contain specific diagnoses enabling such factors to be examined. Louis et al. noted the presence of mental illness as a significant risk factor for hospital admission, and Kansagara et al. noted that a diagnosis of mental health comorbidities/mental illness was included as a significant predictor in 9 out of 24 models used to predict readmission.

A global self-reported item of health status (as in item 1 of the Short Form 36 Health Survey) has been included in some self-report models, with some indications of evidence to support its use (see page 18). However, a wide variety of health status and health-related quality of life instruments have been used, and which instrument is chosen will depend on the type of prediction model (e.g. whole of population, elderly focus, disease specific model). Including such items may be useful, but they depend on a self-report
component or otherwise one would need to include such an item in the discharge form or in the GP data system. If, as an interim step, a model that combined self-report data and admissions data was utilised, such an item could be tested.

Items concerning functional status are rarely included in risk models predicting hospital admission, although they are more commonly included in models that focus on the elderly (e.g. Lyon et al.) or in models concerned with predicting readmission. Similar findings apply to the inclusion of items concerning long-term disability and the presence of cognitive impairment. This raises the issue as to whether it is worthwhile to include such factors in ‘whole of population’ risk stratification approaches or whether customised models for the prediction of particular outcomes (e.g. admission, readmission, LOS) should apply. Presumably in more inclusive whole of population approaches, if such items are included, they can be calibrated to the particular outcomes under study. In considering factors such as cognitive impairment, it is worth remembering that the Australian population is ageing.

Polypharmacy and multiple medication use were included in 11 prediction models for hospitalisation; 9 models also examined the use of specific medications; and 1 model examined potentially inappropriate prescriptions. Most of the previous review articles indicate that polypharmacy or the use of three or more medicines is a strong risk factor for hospital admissions, and a number of the predictive risk models for hospital admission and ED attendance include prescription data and identify medication use as an important risk factor. However, Kansagara et al. noted that few readmission predictive models examined medication use, although some studies noted that some types of drugs (anticholinergics and sedatives) can affect physical function and also be associated with an increased LOS. Overall, there is sufficiently strong evidence to include multiple medication use as a predictor in risk stratification models.

Biomedical markers such as blood pressure and blood cholesterol were rarely included in generic risk stratification models but are more frequently included in disease specific models.

BMI has been investigated with conflicting findings in a number of research studies (see page 25). Korda et al. found a dose response relationship between above normal BMI and hospital costs, admissions and bed days when compared with normal BMI, but they did not examine those with low BMI. Some studies have indicated being underweight as an important factor for readmission. However, Hainer and Aldhoon-Hainerova and Zekry in their reviews noted that despite obesity being recognised as a major risk factor for CVD and diabetes, there was some evidence for the ‘obesity paradox’ – that a higher BMI may be associated with a lower mortality and better outcome in several chronic diseases for elderly persons. It is likely that BMI may have an unusual distribution, which may help to explain the above findings. However, the current evidence is equivocal for BMI, and as such other indicators might be preferred for the inclusion in a risk stratification model.

Population health studies indicate that smoking is a major risk factor for a number of diseases, and Tran et al. found that non-smoking was significantly associated with a reduced risk of PPH. However, other research studies indicated conflicting findings for smoking status with regard to hospital admissions and readmissions. Similarly, there is ample evidence for an association between high levels of alcohol consumption and some chronic diseases, and recent research suggests that risky alcohol consumption may be responsible for 430 hospitalisations per day in Australia. However, Tran et al. found that lower alcohol consumption was associated with an increased risk for PPH, and in this context they noted a J
distribution for this variable. In the Tran et al. study, people were asked to report on recent alcohol consumption rather than lifetime consumption, which may potentially identify a more positive association. This period of exposure may also be an issue to explore with smoking status. Measurement of these risk factors is complex and further thought is required concerning the best ways to measure these variables.

Tran et al. found that having sufficient physical activity reduced the multivariable adjusted risk of PPH (HR=0.74). They also found that sitting for less than eight hours per day reduced the risk of PPH (HR=0.86). A few studies have indicated that physical activity factors are related to risk of readmission to hospital. Most predictive models do not include indicators of physical activity or inactivity, but some include indicators of mobility.

Regarding nutrition, the Tran et al. survey items concerning the daily consumption of fruit and vegetables showed no significant association with risk for PPH. The problem with this variable is that only 23% of the sample was defined as having adequate nutrition, so the measurement of nutrition or malnutrition may require further thought. A number of studies report increased hospitalisation, LOS and costs for those with poor nutrition, but the Carpenter et al. review found no increase in adverse outcomes for ED admitted patients (e.g. ED return assessed by the Mini Nutritional Assessment Short Form). While nutrition appears to be an important risk factor, methods to assess nutrition in research studies usually require an assessment of about ten minutes.

In conclusion, this evidence check aligns well (see Table 2 and Table 3) with proposed social and clinical risk factors identified in the ACI paper on risk stratification. However, some caution should be used when considering the ‘strength’ of risk factors identified from the Muenchberger et al. study which ACI cites. Although Muenchberger et al. make many statements, such as “multiple studies (n=27) identified the important role of health status (including physical and mental) and health-related quality of life in the prevention of hospitalisation”, we found only a small proportion of these studies were actually discussed (n=6). It was also not possible to identify the remaining 21 papers due to the lack of a direct citation. Thus, it was impossible to verify the significance of findings for such papers or to identify whether these were papers that only mentioned the variable under discussion. This may have been an oversight by the authors, but as a result it was not possible to interrogate or replicate these findings.
6 Disease specific risk stratification approaches

This section provides a brief overview of disease specific risk stratification models. A thorough investigation of these models is outside of the scope of this literature review; however, this section will provide a general impression of current developments in this field. We investigated one literature review and 12 disease specific risk stratification studies, of which seven centred on cardiovascular conditions, two on respiratory conditions, two on digestive conditions, one on an endocrine condition and one on a musculoskeletal condition.

The statistical methods used to develop disease specific risk stratification models were similar to those used in general population models. Of the 12 disease specific risk stratification studies, seven used univariate analysis followed by logistic regression, two used a refined logistic regression model based on multiple iterations, one used Cox regression, one used recursive partitioning, and one used a risk prediction tool. The AUC statistic was used to describe model discrimination for 10 out of the 12 studies.

Unlike general population risk stratification models, disease specific models were more often based on a subset population defined by characteristics that were linked to the disease. Of the 12 disease specific risk stratification studies, eight used a population based on disease related factors, two were based on the general population, and two were based on a demographic subset of the general population. Six disease specific risk stratification studies considered models in the community setting, and six studies considered models in the hospital setting.

As in general population risk stratification models, disease specific models often included independent variables such as demographics, comorbidities and prior hospital utilisation. Additionally, they often also considered biomedical markers, medication usage and factors relating to medical interventions.

When considered, biomedical markers were found to be predictive of the dependent variable in 11 out of 12 models (92%), diagnoses and/or comorbidities were found to be predictive of the dependent variable in 17 out of 19 models (89%), medication usage factors were found to be predictive of the dependent variable in seven out of eight models (88%), and prior hospital utilisation was found to be predictive of the dependent variable in ten out of 12 models (83 per cent). Demographic factors were found to be predictive of the dependent variable in only 14 out of 24 models (58 per cent).

Cardiovascular disease models

One literature review and six cardiovascular risk stratification studies were considered in this review. Cardiovascular conditions included heart failure, acute myocardial infarction and arterial fibrillation.
Betihavis et al.\textsuperscript{48} considered six studies about risk prediction models for rehospitalisation of adults with chronic heart failure. They reported that the only common predictors identified by previous studies were a history of diabetes and a history of prior hospitalisation.

Fifteen cardiovascular risk stratification models were included in the six abovementioned studies. Biomedical markers were found to be predictive factors of the dependent variable in all cardiovascular models when included.\textsuperscript{32,207–209} When biomedical markers were not included, diagnoses and/or comorbidities were found to be predictive of the dependent variables.\textsuperscript{120,210} Additionally, prior hospital utilisation was found to be predictive of the dependent variable when included.\textsuperscript{32,208,210} The predictive ability of demographic factors varied across all six studies.

**Other disease groups**

Included in this literature review are two respiratory disease risk stratification studies. The Incalzi et al.\textsuperscript{55} model aimed to predict the LOS for older patients with COPD, and the Schatz et al.\textsuperscript{153} model looked at the relationship between psychometric tools and medical utilisation for patients with asthma. Both studies found prior medication use and demographic factors to be predictive of their respective dependent variables.

Rosella et al.\textsuperscript{213} used two modified versions of the Diabetes Population Risk Tool (DPoRT) to determine whether using a more detailed description of ethnicity could improve the prediction of diabetes risk. The versions used for comparison removed ethnicity and added more detail. Rosella et al.\textsuperscript{213} stated that excluding ethnicity resulted in a decrease in the AUC \(c\) statistic of 0.02 (0.77 for the original DPoRT model and 0.75 for the model without ethnicity). Adding detailed ethnic information did not show any further improvement. In addition to ethnicity, the DPoRT model includes demographic variables and comorbidities.

Two digestive system risk stratification studies were identified: Kelly et al.\textsuperscript{212} looked at predictive factors for readmission following a major gastrointestinal resection, and Saltzman et al.\textsuperscript{178} identified predictors of hospital mortality, LOS and cost for patients with upper gastrointestinal bleeding. Although the variables tested differed, biomedical markers and comorbidities were found to be significant predictive factors in both studies. The biomedical markers and comorbidities identified varied based on the study.

A number of other studies looked at post-medical interventions and the risk of readmission to hospital, in addition to the study on major gastrointestinal resections mentioned above.\textsuperscript{212} Mesko et al.\textsuperscript{214} considered total hip and knee arthroplasties and the discharge destination (to nursing home or place other than home) and found them to be significant predictive risk factors, as were a number of operative items. Kelly et al.\textsuperscript{212} found increased risk for patients whose operative time was greater than four hours, was open or was a pancreatic resection. Mesko et al.\textsuperscript{214} found a higher risk for patients receiving a general anaesthetic or a blood transfusion.

**Chronic disease management interventions**

A literature review by CEHSEU, the Clinical Epidemiology and Health Service Evaluation Unit\textsuperscript{20}, described interventions to reduce potentially preventable hospitalisations (PPH), which may benefit from risk stratification by disease type. In chronic disease, interventions tended to be either multidisciplinary, single discipline or self-managed. Effectiveness was measured by calculating the relative risk (RR) of events such as
hospitalisation and hospitalisation due to the chronic disease. The effectiveness of interventions varied, for example, multidisciplinary intervention for coronary heart disease showed a significant reduction in hospital admissions (RR=0.87). Interventions for COPD reduced emergency/unscheduled hospital visits (RR=0.58) and hospitalisations (RR=0.78)\textsuperscript{20}

Purdy\textsuperscript{3}, in a more recent and very comprehensive review, noted there was sufficient evidence to support case management and specialised clinics, but only for heart failure. There was also weak evidence to support education and self-management interventions but, again, only for heart failure. There some was evidence to support exercise and rehabilitation interventions for COPD. It was also found that telemedicine might have a possible effect on heart disease, diabetes and hypertension, but further evidence was required.

**Conclusion**

Disease specific models include more clinical risk factors and biomarkers in their models and less socio-demographic and social risk factors. The discriminatory performance of the risk stratification models examined (c statistics ranged from 0.50 to 0.76 for readmission) was modest\textsuperscript{207,208,214} and no better than that found for generic models. However, a comprehensive review of all risk stratification models for all diseases or conditions was outside the scope of this review. There is some evidence to support the use of some integrated care interventions for heart failure and exercise-related interventions for COPD, but this evidence was not directly related to risk stratified interventions.
Selecting or developing a generic model

The review of clinical and risk factors considered above should be considered in the development of any risk stratification approach or in the selection of any model which may potentially be adapted to the NSW context.

There are different types of predictive risk models that can be considered. Wallace et al. reviewed models that predict emergency hospital admissions in community dwelling adults, and these models were not contingent on an index hospital admission. These models may be based on self-report data (9 models) or administrative data and/or clinical record data (18 models). Most of these latter models require data linkage across health datasets (e.g. pharmacy, outpatient, inpatient, general practice, ambulance and emergency, community/social services etc.). Eleven models included general practice clinical record data. A recent report indicated that JHU ACG UK should be included with the above models, and a recent review by Haas et al. indicated that this model had the highest c statistic of the models compared for the prediction of hospitalisation.

Generally, the models that include GP data have AUC c statistics above 0.7, indicating a reasonable discriminatory performance. Billings et al. examined four models using a) inpatient data alone b) combined ER and inpatient data c) combined inpatient/ER/outpatient data and d) combined inpatient/ER/outpatient/GP data, and the model including GP data performed the best in predicting admissions in the following year. This model had a c statistic of 0.78 compared with 0.73 for using inpatient data alone. More of these models are also whole of population models and so are not limited to only identifying elders at risk. It can be seen that data linkage can improve discrimination, particularly when including primary care data, but there will be considerable costs and time involved in developing a primary care dataset that can be linked with inpatient, pharmaceutical, A&E and other utilisation datasets available within the NSW context. Some consideration of the substantial costs involved in developing linked datasets and in developing or modifying a risk prediction model would need to be undertaken. In that context, it is worth noting that after years of funding the development of the Combined Predictive Model (CPM) in the UK, the NHS moved to a model where Commissioning Groups could choose their own model (from a recommended set of providers) for risk stratification purposes. Paton et al. noted that funding ceased for the CPM in 2011, but a number of regional models have used CPM as a base and modified the model with the inclusion of local variables such as GP continuity.

Although we agree with ACI that there is no international data model that is currently appropriate for the NSW context, a number of these models are open to adjustment and the inclusion of local context variables. The latest version of JHU ACG indicated that it may be possible to map diagnosis-related groups to the ACG system used in the UK, and this could be further explored. Some further analysis could explore the advantages and disadvantages associated with developing a new risk stratification model versus exploring the possibility of adapting one of the more promising models identified by review articles.
In the interim, one strategy might be to undertake a pilot study with a local health district. This could include data linkage of available datasets combined with a self-report survey of general practice patients, with a follow-up period to examine ACSC admissions and other utilisation factors. This would need to include an anonymous identifier that would enable potential linkage to existing datasets, and it is likely that patient consent would be required. In the Wallace et al.\textsuperscript{69} review, two models which included self-report components were the Lyon et al.\textsuperscript{43} EARLI model and the Damush et al.\textsuperscript{139} model, both of which had adequate discriminatory performance. Potential self-report items could be identified from such models. These models are targeted at elderly community dwelling people, but as a trial/pilot study to identify those who may benefit from integrated care, this could be useful. Further analysis of the APHID dataset may also suggest refinement to the items included.

Kansagara et al.\textsuperscript{68} reviewed models that are used to predict readmission (usually 30-day readmission). These models require an index admission, and for that reason they may be more prone to regression to the mean effects. Readmission models are largely based on hospital administrative data, but this is supplemented by self-report data or chart review in some models. Many of these models had relatively poor discrimination (c<0.7), but the Coleman et al.\textsuperscript{222} administrative model plus self-report model had better discrimination (c=0.83) and included variables such as self-rated health and functional status. What appears to be a variant of the Patients At Risk of Rehospitalisation (PARR model), which uses inpatient data only, is described by Billings et al.\textsuperscript{36} and this appears to have adequate discrimination. Panattoni et al.\textsuperscript{14} suggested the New Zealand National Minimum Dataset could be used to build a NZ equivalent of the PARR model. In the future they suggest it might then be possible to link pharmacy and GP data with hospital data to build an equivalent of the CPM. A similar pilot study could be taken within NSW as another interim step, although it may be worth considering the inclusion of some self-report data, as occurred in the Coleman et al.\textsuperscript{222} model.

The brief review of the recent literature concerning disease specific models indicated they appeared to have no better predictive power than the generic models. As Central Southern Commissioning Support Unit (CSCSU)\textsuperscript{119} noted, multi-morbidity is the norm and is common for those over 45 years. For example, for patients with COPD they found that 89% of them had at least one other long-term condition; for diabetes patients, over 80% had another long-term condition. CSCSU raised the issue that given the increased risks for hospitalisation associated with multi-morbidity, there may be a need to consider providing care in a less disease specific way. ‘Whole of population’ risk stratification models also have the advantage that they can be useful for population profiling, which may inform decisions about the nature and settings of services that need to be provided.

Paton et al.\textsuperscript{220} note that caution is required with regard to the selection of risk prediction models. They note that basic statistical data, such as AUC c statistics, sensitivity and specificity, and positive and negative predictive values, are often not adequately reported for these models, and it is rare for a model to be validated with an external sample separate to the development and split half validation samples. Other statistical issues or concerns have been raised by other authors.\textsuperscript{12,223,224} A problem with some commercial models is the absence of independent published evidence and the difficulty in obtaining cost estimates to compare these models.
8 Integrated care programs and risk stratification

A summary table for the articles discussed below is provided in Appendix 2. It had been noticed by Ham et al., among others, that Kaiser Permanente was one of the US health plans that was routinely reported as having excellent performance. They compared the utilisation of hospital beds in the NHS in England, Kaiser Permanente in California, and the Medicare program in the US and California. Bed day use in the NHS for the 11 leading causes of bed days was three and a half times that of Kaiser Permanente’s standardised rate; almost twice that of Medicare California’s standardised rate; and more than 50% higher than the standardised rate in Medicare in the US. They noted that Kaiser Permanente achieved these results through a combination of low admission rates and relatively short stays. The authors concluded that the NHS could learn from Kaiser Permanente’s integrated approach, its focus on chronic diseases, and its effective management strategies tuned to the level of risk for hospitalisation, the emphasis placed on self-care, the role of intermediate care, and the leadership provided by doctors in developing and supporting this model of care.

To explore this further, Dixon et al. undertook semi-structured interviews with staff of five US managed care organisations, including Kaiser Permanente. They noted that a) competitive pressures between managed care organisations provided an incentive for innovation in management of chronic diseases; b) doctors in these organisations had a strong management role; c) goals were agreed between clinicians and managers, and financial incentives existed to improve care; d) all managed care organisations identified high-risk patients and targeted intensive nurse led outreach care to minimise hospital admissions; and e) multifaceted chronic disease management programs were used, in which self-care and patient education were central features. Light et al., in a discussion article comparing the NHS and Kaiser Permanente, considered that financial and organisational structures within the NHS militated against true integration; that doctors from primary, secondary and tertiary care should be given joint responsibility for managing clinical services; and that commissioning of health services needed to become less hospital centred. These papers indicated that while it is clear the Kaiser Permanente model produced better system level outcomes, it was hard to identify the particular and relative contributions of the various integrated care components to the success of this model.

Such findings, however, provided an impetus for the NHS to invest in the development of risk stratification approaches to identify those at risk for ED admissions and readmissions, and to target integrated care interventions to those most at risk. The PARR (Patients At Risk of Rehospitalisation) model was developed by Billings et al. initially to predict readmission, and in 2006 the final report on the Combined Predictive Model (CPM) was also published. This model took a whole of population approach to risk stratification concerning the risk of hospital admission and is based on a comprehensive dataset of patient information, including inpatient, outpatient, and A&E data from secondary care sources as well as general practice electronic medical records. Although the CPM was decommissioned in 2011, and Commissioning Groups can now select their risk stratification tools from a range of recommended providers, a number of current models such as the Sussex, Devon and Wales models have used the CPM as a base and added relevant local
variables to this model. Many of the following studies in the UK report on the use of such models to identify high-risk patients for proactive case management interventions.

Sonola et al.\textsuperscript{228} reported on the use of the Devon Predictive Model\textsuperscript{39}, which is based on primary and secondary care data sources and is a local adaptation of the CPM. It was used to identify the top 0.5\% and 5\% of patients at risk of ED admission in the following year for all GP practices in South Devon and Torbay. The patient lists derived were reviewed in the practice by a multidisciplinary team and they selected patients for proactive case management on a ‘virtual’ ward. These patients received intensive assessment and care coordination to provide ongoing care and support in their home. Once their condition was stabilised, they were discharged from the virtual ward and received usual care. Although there have been some reductions in hospital ED admissions for most regions since the introduction and use of the predictive risk model (e.g. this drew attention to high-risk patients in the practice) and the virtual wards, attribution to any particular intervention was less clear. Although there were reductions in ED admissions for 2010 and 2011, for the intervention groups associated with the use of virtual wards this was not sustained in 2012, although it is noted that virtual wards were not operating in all practices for the entire year. Changes in governance arrangements also occurred in 2012, so this may have been an atypical year. Torbay and South Devon had high virtual bed occupancy and have also reported a decline in residential placements as more patients remained at home. However, the evidence is at most suggestive and a longer period of study would be required to assess the contribution of the virtual wards.

The Lewis et al.\textsuperscript{229} study aimed to determine whether the use of such virtual wards in the UK led to changes in rates of unplanned hospital admission compared to matched controls, and if so at what cost. The secondary aims were to assess the impact of the intervention on rates of A&E attendance, social care provision, GP practice visits, and the use of community health services. Patients in Croydon, Wandsworth and Devon virtual wards were compared to matched controls from national data. Compared with matched controls, there was no evidence of a reduction in emergency hospital admissions for patients in the six months after starting the intervention. No evidence was found of a reduction in ambulatory care sensitive hospital admissions in this period, nor in mortality. Lewis et al.\textsuperscript{229} observed a reduction in elective hospital admissions and outpatient attendances in the six months after starting the intervention. Both of these findings were significant at the p<0.05 level; however, there was no evidence of an overall reduction in hospital costs.

Baker et al.\textsuperscript{215} used the Nairn Case Finder algorithm (which includes both primary care and secondary service data; AUC c=0.79 ) to match high-risk chronic disease patients in two large GP practices for age, sex, multiple morbidity, and prior hospital outpatient and inpatient activity. They examined outcomes of admission rate, occupied bed days and survival. The Nairn high-risk intervention group received an Anticipatory Care Plan (ACP) and multidisciplinary proactive case management. This also included the rapid provision of home care and transferring patients from hospital to home over 12 months. Survivors from ACP cohort had 510 fewer days in hospital (p=0.02) and 37 fewer admissions (p=0.002) than in the 12 months prior to their intervention, but the smaller reductions observed for the control group were not significant. Mortality rates were similar but fewer ACP patients died in hospital, and hospital bed days for the last three months of life were significantly less for the ACP group. Costs of the program were offset by a reduction in hospital days and a reduction in unplanned hospital admissions. This was really a pilot study as the sample was small, but the authors reported that it is now being implemented in a more widespread manner in Scotland, although further papers were not detected. The Nairn Case Finder is based on the Scottish PARR but adds GP data.
The JHU ACG White Paper\textsuperscript{10}, NHS\textsuperscript{4} and Central Southern Commissioning Support Unit\textsuperscript{219} described the ACG model operating in a substantial number of primary care trusts in the UK, and provided some useful utilisation data for some regions, which has been found useful for planning purposes (see Figures 3 and 4). However, these papers do not provide information concerning the outcomes of risk stratification-based integrated care interventions. JHU ACG\textsuperscript{230} describes a project implemented in GP practices in Leicester City, UK. The ACG system was used to identify the top 2% highest risk cohort over 18 years in their practices so that these could be case managed by means which included allocating each patient an accountable GP, co-producing with the patient a care plan, and reviewing this care plan at regular intervals in order to prevent unplanned admissions. Practices had access to a specific report from the ACG system which identified a high-risk cohort of their adult patients for inclusion in the case management register. Claims were made that the intervention cost was being funded by savings in hospital costs (e.g. reduced admissions), but no figures were provided. A similar report pertaining to Midlands and Lancashire\textsuperscript{231} used ACG stratification with an integrated care, case management intervention. Again, it was claimed that the intervention was being funded by savings in hospital costs (e.g. reduced admissions). However, no statistics were provided and the summary report was vague and prepared by the JHU ACG group, so no independent evaluation data was available concerning the effectiveness of these interventions.

Similarly, the Optum website\textsuperscript{232} provides a case study using the HealthNumerics-RISC tool. This cites the North East Lincolnshire Integrated Care Program in the UK as a successful application of this risk stratification tool. Following risk identification by the tool, there was an integrated care intervention with social, community health and therapist teams, including intermediate care and acute care. They also tracked activity, interventions and outcomes during the intervention phase. They claimed that through reduced A&E attendances and reduced inpatient stays they saved £1.7 million ($3.4 million) in the first nine months of application. They estimated a £3000 ($5900) saving per avoided ED admission. These are commercial product claims – there was no independent evaluation or evidence.

Ham et al.\textsuperscript{233} collated papers from a seminar which discussed a range of case studies and topics relevant to avoidable hospitalisation in the UK: the Kaiser Permanente chronic disease vortex model; Wandsworth community virtual wards; practice-based commissioning; Brent integrated care coordination service (Brent ICCS); and identifying avoidable admissions. The Brent integrated care model used the EARLI index\textsuperscript{43} to screen patients for risk of ED admission. They found that EARLI was shown to identify, relatively accurately, those at risk of an admission and therefore those most likely to benefit from their integrated care coordination service. Brent ICCS believed this was a key factor in achieving savings – which included a substantial reduction in bed days and ED admissions, and a reduction in falls and delayed transfers to nursing care. This approach sounded quite promising but it was not documented with figures or evidence.

Roland et al.\textsuperscript{234} provided the quantitative results from a multi-method evaluation of six of the UK integrated care demonstration projects which used risk profiling tools to identify older people at risk of emergency hospital admission, combined with intensive case management for people identified as at risk. The interventions focused mainly on delivery system redesign and improved clinical information systems. Most staff thought that care for their patients had improved. More patients reported having a care plan, but they found it significantly harder to see a doctor or nurse of their choice and felt less involved in decisions about their care. The case management interventions were associated with a 9% increase in emergency admissions. Roland et al.\textsuperscript{234} found significant reductions of 21% and 22% in elective admissions and outpatient attendance in the six months following an intervention, and overall inpatient and outpatient costs were significantly reduced by 9% during this period.
Roland and Abel in a follow-up paper suggest that the strategy of focusing only on the high-risk individuals identified by such models when providing integrated care interventions fails to appreciate that high-risk patients don’t account for most admissions. Most admissions come from patients with lower risk levels, and thus the greatest effect on admissions will be made by reducing risk factors in the whole population – a point which ACI has also raised. They noted, however, that while integrated care pilot studies are in progress that use a broader sample of elderly patients, the cost-effectiveness of these more broadly based population approaches has yet to be established.

Goodwin et al. examined seven international case studies concerning the implementation of integrated care for older people with complex needs. This paper was mainly about organisational factors concerning the implementation of large scale integrated care programs, rather than on risk strategies for identifying those who may benefit from integrated care approaches. Only three of the case studies included risk stratification. Torbay UK used the Devon Predictive Model, the Canadian PRISMA initiative included risk stratification based on a staged functional assessment, and the US Massachusetts General Hospital study used a Hierarchical Condition Category model. For five case studies, including these three, it was suggested there may be reductions in hospital admissions and acute episodes of hospitalisation.

In the US, Ferris et al. reported a Care Management for High-Cost Beneficiaries demonstration project (CMHCB) with Massachusetts General Hospital and Massachusetts General Physicians Organization (MGH). High-cost beneficiaries were identified using Hierarchical Condition Categories and cost. These were compared to a similar high-cost group of patients that visited other Boston medical centres and they were matched by age, sex, several common chronic conditions, risk score and cost. The care management intervention included annual assessment and care plan review, telephone monitoring, surveillance calls, pharmacy review, assistance with transitions, advanced care directives and end of life counselling, facilitated communication between team members, urgent response and facilitated office access, psychosocial evaluations and management. Although initially for six months, the intervention was more costly and it reached a break even point at 16 months. After two years, the estimated cost savings were 4.3% or $US6 million ($7.7 million), and savings increased to 4.7% over the next nine months. The authors noted the reduction in admissions for intervention patients as a contributor to cost (no actual figures were provided), but post-acute admissions were similar for both groups.

The final report for the above project was published by McCall et al. The principal objective of the CMHCB demonstration was to test a pay for performance contracting model and multi-component case management intervention strategies for Medicare fee for service beneficiaries who were high-cost and/or who had complex chronic conditions. MGH developed a series of clinical dashboards using data from its electronic medical record, claims data and enrolment tracking database. The dashboards allowed MGH to examine trends in health care utilisation and outcomes. Examples of dashboard indicators were the number of assessments completed within 90 days, number of referrals or interventions conducted, and number of participants screened for depression etc. The report presented findings which suggested an improvement on most of the outcomes including acute care utilisation. It was successful in reducing the rate of increase in acute care hospitalisations and ED visits but not 90-day readmissions. The study claimed substantial and significant cost savings for both the original (12%) and refresh (16%) intervention groups.

Another US study by Boult et al. used a risk stratification model to identify patients at high risk of hospitalisation. Eligible patients 65 years and over who were identified as being at high risk of hospitalisation were randomly allocated to guided care or usual care after risk assessment using the
Hierarchical Condition Category predictive model. This was based on insurance claims data over the 12 months prior to the study. Guided care included comprehensive assessment, a care guide/action plan, monthly monitoring, smoothed patient transitions across care sites, coordinated service provision, promoted patient self-management, educated carers and facilitated access to community resources. Outcomes were the use of ED, hospitals, home health agencies, primary care physician and specialist physician services over the study period of 20 months. They found the only significant difference was that guided care reduced the use of home health care, but had little effect otherwise on health service utilisation over the follow-up period. Guided care showed a 75% probability of a 10% reduction in 30-day readmissions and it reduced use of days in nursing homes. While the latter factor failed to reach significance as these were relatively rare events for this sample size, substantial costs reduction occurred. Basically, the sample size had inadequate power to detect significant differences for such rarely occurring variables. The authors noted that guided care reduced skilled nursing facility admissions, but only for Kaiser Permanente patients (six teams in three practices). Kaiser Permanente practices have a long-term culture of integrated care and an electronic medical record, which the authors felt may potentially be associated with this.

An earlier paper by Boyd et al.\textsuperscript{238} referring to the same study found that the guided care patients had twice the odds of rating their chronic care highly compared to control patients. Another paper by Leff et al.\textsuperscript{239} reported the initial results concerning health service utilisation for this study, which were more promising than those later reported by Boult et al.\textsuperscript{237}

Counsell et al.\textsuperscript{152} reported that GRACE (Global Registry of Acute Coronary Events) trial patients 65 and over and with low income in six community based centres were randomised to receive the intervention or be a usual care control. The intervention involved two years of home-based management care by a nurse practitioner and social worker who collaborated with the primary care physician and a geriatrics interdisciplinary team; they were also guided by 12 protocols for common geriatric conditions. The cumulative ED visit rate was significantly lower for the intervention group, but the hospitalisation rate did not differ across the groups. A sub-analysis was conducted of a predefined group at high risk of hospitalisation (as determined by the Pra model and containing both intervention and control subjects), and this indicated that ED visits and hospitalisations were lower for intervention patients in the second year. There was also evidence for improved self-rated health status (mental, social, vitality) but not physical health status, and there was no difference found in ADL function. There was no examination of cost-effectiveness.

Enard et al.\textsuperscript{203} identified primary care related-avoidable ED visits at ED triage (levels 3–5 non-urgent) and asked patients to join a patient navigation group or comparison group. They examined prior ED utilisation data for the groups and follow-up data for the following year and then for a further year. The intervention had no effect on very frequent ED visitors (three or more visits in the prior two years). For intervention patients with less prior ED utilisation there was a significant reduction in ED visits for the first year but not for the second year.

Levine et al.\textsuperscript{240} assessed the efficacy of a home care program (Choices for Healthy Aging [CHAI]) designed to improve access to medical care for older adults with multiple chronic conditions who were at risk for hospitalisation as compared with usual care. Potential participants were identified from a pool of patients by using an electronic risk assessment screening process, which identified frail older adults at high risk for use of medical services by using an algorithm that considered variables such as age, sex, number of medications, number and types of chronic conditions, and use of ED and inpatient hospital services. CHA patients were less likely than usual care patients to be admitted to hospital during the 12 month
intervention period (one or more bed days 25.6% and 37.1%, respectively; p=0.02). The intervention group reported significantly greater satisfaction with care than usual care recipients (t test=2.476; p=0.014). There were no differences in terms of estimated costs of care between the groups. The authors queried the effectiveness of the risk stratification method used to identify those requiring an integrated care intervention.

In Canada, a tiered/staged assessment system is used to identify elders at risk for hospitalisation. Hebert et al.\textsuperscript{161,241,242} report that the PRISMA system used in Canada involves six components: 1) co-ordination between decision-makers and managers; 2) a single entry point; 3) a case management process; 4) individualised service plans; 5) a unique assessment instrument based on the clients’ functional autonomy; and 6) a computerised clinical chart for communicating between institutions for client monitoring purposes. A single entry point is accessed by phone or written referral. A brief needs assessment (Sherbrooke Postal Questionnaire) is performed. If patients are eligible they are assessed using a seven question screening instrument (PRISMA-7).

The PRISMA items include age over 85 years, male gender, presence of activity limiting health problems, the regular need for a carer, whether the client has a carer, whether health problems require the person to stay at home, and whether the client uses a cane, walker or wheelchair.\textsuperscript{241} The PRISMA tool is used to triage eligible clients and develop a service plan. The case manager is fully involved and is the centre of care coordination. The Functional Autonomy Measurement System (SMAF), a functional profile assessment tool, is then used to measure a client’s resources, disabilities and handicaps. The SMAF includes seven ADL items, six mobility items, three communication items, five mental function items and eight IADL items, and an ISO-SMAF casemix class is assigned. A computerised clinical chart is created for each patient that all physicians have access to update, and this is shared between all physicians in the client’s service continuum.

A pilot study was conducted for which the entry criteria were age 65+, moderate to severe disability (SMAF score), good potential to stay at home, and the need for two or more health care/social services. The main outcome of the pilot study found that study subjects with moderate to severe disability were less likely to experience functional decline than controls at two months (p=0.002), which tended to remain at 24 months (p=0.066 trend only). No association was found for those with mild disability. The authors state that risk of rehospitalisation within 10 days after discharge was significantly greater in the control group, but they did not report the p value. The risk of institutionalisation tended to be greater among controls (RR=1.44, p=0.06).

Stewart et al.\textsuperscript{123} conducted a review of PRISMA studies and reports. There was a reduction in both the incidence and prevalence of ‘functional decline’ among patients exposed to the PRISMA intervention, with a lower annual incidence of functional decline of 137 cases per 1000 individuals in the PRISMA group.\textsuperscript{243} The program also demonstrated a progressive reduction in handicap levels\textsuperscript{244} and a decreased prevalence of unmet needs for those living in the community.\textsuperscript{243,245} Clients reported significantly improved feelings of satisfaction (p<0.001)\textsuperscript{244} and empowerment (p<0.001).\textsuperscript{245} The proportion of clients in the PRISMA intervention group that consulted with a medical specialist once a year dropped from 60% to 50% (p<0.001), whereas the comparative groups remained steady at 60 per cent.\textsuperscript{244} There was no demonstrated difference in rates of hospitalisations, LOS, or readmissions, or in the use of home care or volunteer services.\textsuperscript{244} Desire for institutionalisation was reduced in the first two years of the study but not in the overall four years of the study.\textsuperscript{244} Intervention subjects had fewer nurse and other health professional consultations compared to controls in years three (p<0.001) and four (p<0.001) of the study. Those in the intervention
group were more likely to be admitted after a visit to the ED compared to controls (p=0.043) – possibly due to intervention subjects only going to the ED for serious conditions. Economic benefits showed that for intervention subjects costs reduced, while costs rose for control subjects (p=0.001). Intervention and control subjects both experienced a drop in annual consultation costs, but the intervention group drop was much greater (p=0.006). This was mainly due to, on average, one less specialist consultation per year. Two limitations to the PRISMA research identified by this review were that the Québec health care system was already quite integrated and so the effects may have been reduced, and that the use of the electronic record was not fully investigated. It should be noted that this model is a tiered or staged assessment system for the elderly and is quite unlike the other predictive risk models that have been discussed.

In Australia, the Victorian Health Department started an intervention, the Hospital Admission Risk Program (HARP), based on the Kaiser Permanente risk stratification approach. It included initial risk screening focused on medical risk, past health service utilisation, functional ability, and the social needs of the individual patients followed by a comprehensive needs assessment, appropriate care, and transition planning and management with continuous monitoring and review. The approach is reliant on an index admission, which means it may be subject to regression to the mean effects. The evaluation included comparative analysis of individuals before and after enrolment in HARP, and some comparative analysis of HARP and non-HARP patient cohorts, although the details provided are sparse. The key HARP outcomes were number of ED presentations, unplanned hospital admissions, and LOS in case of unplanned admission episode. In general, HARP intervention patients demonstrated 35% fewer ED presentations, 52% fewer ED admissions and 41% fewer days in hospital (p<0.05) compared with non-HARP patients. It is claimed that the HARP had a positive overall impact on the level of hospital utilisation in Victoria. However, this risk-associated model does not appear to have been validated. The overall data provided is pooled across demonstration projects, summary percentages only are provided, and there were no comparative tables that provided the actual data for the intervention and comparison groups. The statistical analysis appeared very limited and as there is no academic publication relating to this approach, it has not been assessed in prior reviews.

An article by Snyderman et al. suggested that primary care physicians could make use of some of the simpler risk stratification approaches (e.g. Pra, LACE index) to assist in reducing readmissions. However, Sonola et al. noted some resistance by GPs in using summaries derived from the Devon model for high-risk patients. This was due to the model identifying people who had recently been hospitalised and who were now recovering, and the failure of the model to identify some people who were considered at high risk by the practice. As a result, the practices were able to add patients to the high-risk list identified by the model. As these more sophisticated models are complex, attention may need to be paid to educating practitioners about how these models work as otherwise they may be distrusted as representing a ‘black box’ phenomena.

It should be noted that relatively few studies were found that evaluated the outcomes of integrated care interventions where risk stratification models had been used to identify patients at high risk for hospitalisation. This may reflect the emerging nature of this field of study. The strength of evidence ranged from anecdotal evidence through to RCTs, but there was relatively little high-grade research. Despite a few promising studies, overall the evidence suggests that the outcomes for most of these interventions were modest and the primary desired outcome of a reduction in hospital admissions was rarely achieved. It is difficult to determine from this limited literature whether this reflects that the risk stratification models used were not very effective in targeting those in most need of integrated care, or whether it reflects that the
integrated care interventions themselves (e.g. virtual wards, case management etc.) were not particularly effective. However, recent initiatives in the NHS\textsuperscript{41} to supplement risk stratification with approaches such as frailty assessment and impactibility assessment (e.g. identify high-risk patients for whom the proposed assessment is likely to have an impact) suggests the performance of these models may be only moderately successful.

A systematic review by Purdy et al.\textsuperscript{3} examined integrated care interventions which included controlled studies, controlled clinical trials, controlled before and after studies, and interrupted time series studies. Roland\textsuperscript{248} succinctly summarised the following points about these integrated care interventions from this study:

- Case management – overall no effect except for heart failure
- Specialist clinics – overall no effect except for heart failure
- Care pathways and guidelines – no effect but limited evidence
- Medication review – no effect but limited evidence
- Education and self-management – weak evidence for heart failure
- Exercise and rehabilitation – effective in COPD
- Telemedicine – possible effect on heart disease, diabetes, hypertension and older people
- Hospital at home – increased readmissions.

A few more recent systematic review studies were detected. Health Quality Ontario\textsuperscript{249} indicated some minor reduction in admissions for those using home care support services. It also indicated that specialised nurses working with doctors could reduce hospital visits, but this evidence was based on a very small sample of studies.\textsuperscript{249} Huntley et al.\textsuperscript{251} examining case management interventions reported there was no reduction in admissions for 9 out of 11 intervention studies examined. Kruis et al.\textsuperscript{252}, concerning integrated disease management interventions for COPD, reported a small decline in bed days for these interventions. Panagioti et al.\textsuperscript{253} reviewed 184 studies and identified that only a minority of self-management interventions reported a decline in health care utilisation. Coulter et al.\textsuperscript{254} submitted a protocol for undertaking a review of care coordination interventions for the management of chronic disease, but this review is unavailable as yet.

Overall, the evidence considering the effectiveness of integrated care interventions indicated there are fairly limited benefits identified for many of these interventions, and there is a limited effect on the avoidance of hospitalisation.
9 Conclusion

The review resulted in the identification of some important predictors related to the demographic, social, clinical and biochemical profile of patients which can be included in risk stratification systems for NSW (refer to Sections 4.1 and 4.2). However, caution should be exercised as some of the factors have issues with measurement (such as smoking status and alcohol consumption) and generic versus disease specific applicability (biomedical markers such as blood pressure).

Some of these factors (e.g. functional status, cognitive impairment) were more often included in models predicting outcomes such as readmission and LOS than PPH. Thus, for each desired outcome the best predictors may be slightly different, and any model utilised would need to be adjusted in relation to the outcome being assessed.

Overall, this evidence check largely supports the potential risk factors that were identified by the ACI^2 risk stratification review study. However, we note that each factor needs to be assessed independently rather than as clusters of factors as indicated by ACI^2 (e.g. smoking, alcohol use, other drug use).

In developing a model for risk stratification purposes, further consideration needs to be given to whether to adapt or modify an existing approach or to develop a new model. There are now a wide variety of risk prediction models available, although many of them require further and ongoing validation. It is important to note that while the reported predictive power of models is broadly similar, the underlying populations, data sources and coding may differ substantially, and this needs to be considered in the review of comparative performance of models. While we agree with ACI^2 that no existing model is currently suitable to the NSW context, we noted that there are a number of existing models that could potentially be adapted to fit this context. Some of these models take a whole of population approach, others can be used to predict admissions and readmissions or can be focused on population segments, such as those over 65 years. Thus, we feel that some of these models should be explored in more depth. There is a need to consider the relative anticipated costs of model adaptation and development.

Some of the more sophisticated whole of population models require the establishment of a data linkage platform that would benefit from a wide range of data sources and require a considerable economic investment. Given the lack of existing system-wide primary care data collection, one suspects it may take some years to develop. In the interim we have suggested a number of simpler or ‘pilot’ strategies that could be used to trial risk stratification methods (using some data linkage elements) to predict admission with the elderly cohort or with respect to the prediction of readmissions and LOS. Purdy et al. noted that risk tools ranged from simple questionnaires (e.g. EARLI) to large computer based models, but concluded there was no clear advantage of using one type of tool over another. Given the considerable cost factors likely to be involved in the development or modification of a whole of population model, it might be better to start with a simpler and potentially less costly approach. A small-scale, grassroots application that is close to the user may be a better approach to initially explore the applicability of predictive models in NSW, rather than to start with a large scale, top-down approach. Additionally, a model that can be customised to local circumstances would be preferable as most models that are developed in other countries are based on their demography, social circumstances, and epidemiological and health care utilisation patterns.
This review found that there was very limited evidence that risk stratification associated with integrated care interventions systematically produced better system level outcomes, such as reduced ED visits, hospital admissions, readmissions or LOS. Admittedly, this is a new field of research, but the evidence to date is underwhelming and equivocal in its findings. This probably reflects the nature of evidence to support the effectiveness of integrated care interventions in general, which has shown only modest benefits in some specific areas to date.\(^3\) Given this, we feel that the investment required for building a whole of population model would be hard to justify for the purposes of just targeting integrated care interventions. The NHS\(^4,119\) has suggested a broader range of applications for data arising from such whole of population models, such as population profiling, disease analysis, the benchmarking of casemix adjusted outcomes, planning, budgeting and funding distribution/resource allocation. However, many of these activities are currently undertaken using existing datasets (e.g. casemix adjusted outcomes analyses in the rehabilitation sector), so the issue may be to what extent a whole of population approach might add value to existing initiatives. Given the potential costs, these potential benefits need to be carefully considered in the NSW and Australian context.

As Lewis et al.\(^5\) comment, the predictive accuracy of many risk stratification tools is modest, and one needs to consider both the potentially adverse and beneficial effects of screening when targeting interventions. There is an ethical imperative to implement predictive risk modelling in ways that ensure that benefits are not unduly targeted to a specific population group to safeguard fair and equitable allocation of resources.

An advantage of predictive risk models is that the threshold can be varied to examine these factors and their cost implications – but the benefits of the model must outweigh the costs. Some strategies to improve the impact of risk stratification such as impactibility (additionally identify those high-risk people for whom the intervention may have the most impact) could potentially worsen health inequalities if they are applied inappropriately.\(^255,256\) Many of the interventions offered in risk stratification programs appear to increase cost, and as there is a lack of robust evidence to support hospital avoidance programs to date, further research is required.


57. Miller Y. Development of a chronic disease risk factor index in the NSW Health Survey Program. 2003, NSW Centre for Physical Activity and Health, University of New South Wales: Liverpool.


59 TARGETING INTEGRATED CARE TO THOSE MOST LIKELY TO NEED FREQUENT HEALTH CARE: A REVIEW | SAX INSTITUTE


119. Central Southern Commissioning Support Unit NHS, Overview of the ACG® System. 2014, Central Southern Commissioning Support Unit, NHS.


195. Foundation for Alcohol Research and Education, Foundation for Alcohol Research and Education Annual Alcohol Poll: Attitudes and Behaviours. 2014, Foundation for Alcohol Research and Education; Deakin, ACT.


217. Sussex Health Informatics Service, Sussex Combined Predictive Model (Sussex CPM). 2013, Sussex Health Informatics Service,.


227. Billings J, Mijanovich T, Dixon J. Case finding algorithms for patients at risk or re-hospitalisation: PARR1 and PARR2. . 2006, King’s Fund Health Dialog Analytic Solutions, NYU Center for Health and Public Service Research.


246. Roland M. Reducing emergency admissions: are we on the right track? 2012 accessed 20 April 2015; Available from: https://www.rcplondon.ac.uk/sites/default/files/03_-_martin_roland.pdf


Appendices

Appendix 1: Strength of evidence

1. **Well-supported practice**: Evaluated with a controlled trial (including cluster control) and reported in a peer-reviewed publication with no major design flaws evident*; systematic literature review including an appropriately conducted meta-analysis

2. **Supported practice**: Evaluated with a controlled trial group and reported in a journal or at least a government report or similar*; systematic and/or comprehensive literature review

3. **Promising practice**: Evaluated with a comparison to another comparable health system or service or group; review or discussion article supported by a search strategy that includes the key papers

4. **Acceptable practice**: Evaluated with an independent assessment of outcomes, but no comparison group (e.g. pre- and post-comparisons, post-reporting only or qualitative methods)

5. **Emerging practice**: Evaluated without an independent assessment of outcomes (e.g. formative evaluation, qualitative evaluation conducted internally); reviews/discussion articles which include some key papers but with limited information concerning the search strategy

6. **Routine practice** (e.g. small scale and limited statistical analysis of routine data for a service)

7. **Expert opinion** (e.g. peak bodies, government policy, individual opinion pieces)

8. **Case study** (e.g. one-shot case studies or a group of case studies that are largely anecdotal)

9. **Other** (e.g. psychometric analyses, economic evaluations, large scale analysis of administrative/health system data, service utilisation studies, burden of disease).

*Where a controlled trial has design or implementation issues, this will be noted and the strength of evidence classification will be lessened.
## Appendix 2: Risk stratification and integrated care interventions

<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baker et al.</td>
<td>2012</td>
<td>Anticipatory care planning and integration</td>
<td>Cohort study with control group</td>
<td>Acceptable practice</td>
<td>ACP cohort N=96 of which 80 survived; control cohort N=96 of which 81 survived</td>
<td>Used the Nairn Case Finder algorithm (includes both primary care data and secondary service data; AUC c=0.79) which matched high-risk chronic disease patients for unplanned admission in two large GP practices for age, sex, multiple morbidity and prior hospital outpatient and inpatient activity. Examined the outcomes of admission rate, occupied bed days and survival. The Nairn high-risk patients received an Anticipatory Care Plan and multidisciplinary proactive case management, which also included rapid provision of home care when transferring patients (if admitted) from hospital to home over 12 months. The mean age of the study subjects was about 80 yrs. Survivors from the ACP cohort had 510 fewer days in hospital (p=0.02) and 37 fewer admissions (p=0.002) than in the 12 months prior to their intervention, but the smaller reductions observed for the control group were not significant. Mortality rates were similar, but fewer ACP patients died in hospital and hospital bed days for the last 3 months of life was significantly less for ACP. Costs of program were offset by a reduction in hospital days and a reduction in unplanned hospital admissions. Really a pilot study but the authors state it is now being implemented in a more widespread manner in Scotland. Nairn Case Finder is based on Scottish PARR model but adds GP data.</td>
<td>Scotland</td>
<td>Jnl</td>
<td></td>
</tr>
<tr>
<td>Boult et al.</td>
<td>2011</td>
<td>The effect of guided care teams on the use of health services</td>
<td>Cluster RCT; guided vs. usual care</td>
<td>Supported practice</td>
<td>850 patients randomised to guided care: 446 or usual care: 404</td>
<td>Eligible patients 65 years and over at high risk of hospitalisation were randomly allocated to guided care or usual care after risk assessment using Hierarchical Condition Category predictive model, which is based on insurance claims data over the 12 months prior to the study. Guided care included comprehensive assessment, a care guide/action plan, monthly monitoring, smoothed patient transitions across care sites, coordinated service provision, promoted patient self-management, educated carers and facilitated access to community resources. Outcomes included were use of ED, hospitals, home health agencies, primary care physician and specialist physician services over the study period of 20 months. They found the only significant difference was that guided</td>
<td>US</td>
<td>Jnl</td>
<td></td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>----------------</td>
</tr>
<tr>
<td>Boyd C et al.</td>
<td>2009</td>
<td>The effects of guided care on the perceived quality of health care for multi-morbid older persons: 18 months outcomes from a cluster RCT</td>
<td>Cluster RCT; guided vs. usual care</td>
<td>Supported practice</td>
<td>904</td>
<td>Eligibility based on risk for incurring high health care costs in coming year based on analysis of recent insurance claims, randomised to usual or guided care. Guided care condition integrated an RN trained in chronic care into the primary care practice to provide comprehensive chronic care. After 18 months, guided care patients had twice the odds of rating their chronic care highly. Most significant factors were related to goal setting, coordination of care and decision support. See Boult et al. study above.</td>
<td>Patient feedback – see Boult et al. study</td>
<td>US</td>
<td>Jnl</td>
</tr>
</tbody>
</table>

Care reduced the use of home health care, but had little effect otherwise on health service utilisation over the follow-up period. Guided care showed a 75% probability of a 10% reduction in 30 day readmissions. It reduced use of days in nursing homes, but the latter factor failed to reach significance as this is a relatively rare event in this sample size. However, substantial costs reduction occurred. Basically the sample size had inadequate power to detect significant differences for such rarely occurring variables. Noted that guided care reduced skilled nursing facility admissions but only for Kaiser Permanente (KP) patients (6 teams in 3 practices). KP practices have a long-term culture of integrated care and an electronic medical record, which may potentially be associated with this.
<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literatue type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counsel SR et al.</td>
<td>2007</td>
<td>Geriatric care management for low income seniors</td>
<td>RCT</td>
<td>Supported practice</td>
<td>Intervention: 474, controls: 477</td>
<td>GRACE trial patients 65 and over and with low income in 6 community based centres were randomised to receive the intervention or be a usual care control. This intervention involved two years of home-based management care by a nurse practitioner and social worker who collaborated with the primary care physician and a geriatrics interdisciplinary team, and were guided by 12 protocols for common geriatric conditions. The cumulative ED visit rate was significantly lower for the intervention group, but the hospitalisation rate did not differ across the groups. A sub-analysis conducted of a predefined group at high risk of hospitalisation (using the Probability of Repeated Admissions model – containing both intervention and control subjects) indicated that ED visits and hospitalisations were lower for intervention patients in the second year. There was also evidence for improved self-rated health status (mental health, social, vitality) but not physical health status and no differences in ADLs. No examination of cost-effectiveness.</td>
<td>Risk stratification and intervention analysis</td>
<td>US</td>
<td>Jnl</td>
</tr>
<tr>
<td>Enard KR et al.</td>
<td>2013</td>
<td>Reducing preventable ED utilisation and costs by using community health navigators</td>
<td>Non-equivalent comparison group quasi-experimental design; pre–post</td>
<td>Emerging practice</td>
<td>1905 intervention subjects and 11,737 controls</td>
<td>Identified primary care related-avoidable ED visits at ED triage (levels 3–5 non-urgent) and asked patients to join a patient navigation group or comparison group. Examined prior ED utilisation administrative data for the groups and follow-up data for the following year. The intervention had no effect on very frequent ED visitors (3+ visits in the prior 2 years). For intervention patients with less prior ED utilisation there was a significant reduction in ED visits for the first year, but not for the second year. Some issues with data analysis and research design.</td>
<td>ED risk triage</td>
<td>US</td>
<td></td>
</tr>
<tr>
<td>Ferris TG et al.</td>
<td>2011</td>
<td>Cost savings from managing high-risk patients</td>
<td>Matched comparison group</td>
<td>Promising practice</td>
<td>2619 intervention patients, control group size unclear</td>
<td>Discusses a Care Management for High-Cost Beneficiaries demonstration project (CMHCB) with Massachusetts General Hospital and Massachusetts General Physicians Organization. High-cost beneficiaries were identified using Hierarchical Condition Categories and cost. These were compared to a similar high-cost group that visited other Boston medical centres and were matched by age, sex, several common chronic conditions, risk score and cost. The care management intervention included annual assessment and care plan review, tele-monitoring, surveillance calls.</td>
<td>Stratified for multi-component managed care intervention</td>
<td>US</td>
<td>Jnl</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>------------------</td>
<td>------</td>
<td>----------------------------------------------------------------------</td>
<td>-----------------------</td>
<td>----------------------</td>
<td>------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Goodwin N et al.</td>
<td>2014</td>
<td>Providing integrated care for older people with complex needs; lessons from 7 international case studies</td>
<td>Review/discussion article</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Examined 7 international case studies concerning the implementation of integrated care for older people with complex needs. Mainly about organisational factors concerning the implement of large scale integrated care programs rather than on risk strategies for identifying those who may benefit from integrated care approaches. Only 3 case studies included risk stratification. Torbay UK used the Devon Predictive Model, the Canadian PRISMA initiative included risk stratification based on a functional assessment, and Hierarchical Condition Categories was used by US Massachusetts General Hospital. For 5 case studies including these 3 and HealthOne in Australia, there was a suggestion that there may be reductions in hospital admissions and acute episodes of hospitalisation.</td>
<td>Useful lessons concerning the implementation of integrated care approaches but limited mention of risk stratification approaches</td>
<td>UK</td>
<td>Grey</td>
</tr>
<tr>
<td>Ham C et al.</td>
<td>2010</td>
<td>Avoiding hospital admissions: lessons learnt from experience</td>
<td>Seminar papers</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Seminar which discusses a range of case studies and topics relevant to avoidable hospitalisation in the UK: the KP chronic disease vortex model; Wandsworth community virtual wards; practice-based commissioning; Brent integrated care coordination service (ICCS); identifying avoidable admissions. Braithwaite noted the Brent integrated care model used the EARLI index to screen patients for risk of ED admission. Braithwaite claimed that EARLI has been shown to identify, relatively accurately, those at risk of an admission and therefore those most likely to benefit. Brent ICCS believed this has been the key to achieving savings – which Brent ICCS used EARLI model, but only anecdotal evidence</td>
<td>Brent ICCS used EARLI model, but only anecdotal evidence</td>
<td>UK</td>
<td>Grey, King’s Fund Seminar Report</td>
</tr>
</tbody>
</table>

pharmacy review, assistance with transitions, advanced directives and end of life counselling, facilitated communication between team members, urgent response and facilitated office access, psychosocial evaluations and management. Although initially for 6 months, the intervention was more costly; it reached break-even point at 16 months. After 2.0 years, estimated cost savings were 4.3% or $US6 million ($7.7 million) and savings increased to 4.7% over the next 9 months. Also noted the reduction in admissions for intervention patients as a contributor to cost savings, but no admission rate figures provided. Admissions from post-acute settings were similar for both groups.
<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ham C et al.</td>
<td>2003</td>
<td>Hospital bed utilisation in the NHS KP, and the US Medicare program: analysis of routine data</td>
<td>Analysis of routine admissions data</td>
<td>Other: systems data, comparative performance</td>
<td>Admissions for 2001 and 2002 for those &gt;65</td>
<td>Included a substantial reduction in bed days and ED admissions, reduction in falls and delayed transfers to nursing care. Unfortunately, no figures are provided.</td>
<td>Comparison of NHS, KP and Medicare US</td>
<td>UK</td>
<td>Jnl</td>
</tr>
<tr>
<td>Herbert R et al.</td>
<td>2003</td>
<td>PRISMA: a new model of integrated service delivery for frail older people in Canada</td>
<td>Pilot study: 2 cohorts – intervention and control – followed for 3 years (1997–2000)</td>
<td>Promising practice</td>
<td>Intervention =272, controls = 210</td>
<td>In Canada, a tiered/staged assessment system is used to identify elders at risk for hospitalisation. Herbert et al. reported that the PRISMA system used in Canada involves 6 components: (1) coordination between decision-makers and managers, (2) a single entry point, (3) a case management process, (4) individualised service plans, (5) a unique assessment instrument based on the clients’ functional autonomy, and (6) a computerised clinical chart for communicating between institutions for client monitoring purposes. A single entry point is accessed by phone or written referral. A brief needs assessment (Sherbrooke Postal Questionnaire) is performed. If patients are eligible they are then assessed using a 7 question screening instrument (PRISMA-7). The PRISMA tool is used to triage eligible clients and to develop a service plan. The case manager is fully involved and is the centre of care coordination. The SMAF assessment tool (a functional profile) is then used to measure a client’s resources, disabilities and handicaps. The SMAF includes 7 ADL items, 6 mobility items, 3</td>
<td>Tiered risk assessment system for the elderly</td>
<td>Canada</td>
<td>Jnl</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Hebert R et al.</td>
<td>2003</td>
<td>Frail elderly patients: New model for integrated service delivery</td>
<td>Same as above</td>
<td>Other: Descriptive paper</td>
<td>As above</td>
<td>Outlines the PRISMA-7 items: (answer Yes or No): Are you 85+? Male? Do you have activity limiting health problems? Do you regularly need a carer? Do health problems require you to stay at home? Do you have a carer? Do you use a cane, walker or wheelchair? The sensitivity and specificity of the PRISMA-7 are 78% and 75%, respectively, for a cut-off of 3 or more positive answers, and 61% and 91%, respectively, for a cut-off of 4 or more positive answers. This screening tool is used for triage at any entry point. The efficacy of this model has been tested in a pilot project (see above) that showed a decreased incidence of functional decline, a decreased burden for caregivers, and a smaller proportion of older people wishing to be institutionalised.</td>
<td>As above</td>
<td>Canada</td>
<td>Jnl</td>
</tr>
</tbody>
</table>

communication items, 5 mental function items and 8 IADL items, and an ISO-SMAF profile is assigned. A computerised clinical chart is created for each patient that all physicians have access to update and this is shared between all physicians in the client’s service continuum. A pilot study was conducted for which the entry criteria were: age 65+, moderate to severe disability (SMAF score), good potential to stay at home, and the need for two or more health care/social services. The main outcome of the pilot study found that study subjects with moderate to severe disability were less likely to experience functional decline than controls at two months (p=0.002) which tended to remain at 24 months (p=0.066 trend only). No association was found for those with mild disability. The authors state that risk of rehospitalisation within 10 days after discharge was significantly greater in the control group, but they did not report the p value. The risk of institutionalisation tended to be greater among controls (RR=1.44, p= 0.06).
<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hebert R et al.</td>
<td>2010</td>
<td>Impact of PRISMA, a coordination-type integrated service delivery system for frail older people in Québec (Canada): a quasi-experimental study</td>
<td>Quasi-experimental with a pre-test and multiple post-tests for 3 study groups and 3 controls</td>
<td>Promising practice</td>
<td>1501 participants: 728 in intervention, 778 controls</td>
<td>Subjects 75+ years were randomly selected from the Québec Medicare list in 2001 within the 6 study areas. A Sherbrooke Postal Questionnaire was sent out to identify those at risk of functional decline. Positive identifications were those who had 3+ risk factors. The study was extended from 2 years to 4 years as initial recruitment was slow. In total, 1501 persons identified at risk of functional decline were recruited. The eligibility criteria for participants were: aged 75 years or older (77 for the second wave), at risk of functional decline (identified by the SPQ), living at home or in residential facilities within the 6 experimental or comparison areas, and signing an informed consent form. The intervention involved coordination between decision-makers and managers at the regional and local levels, a single entry point, and a common assessment process (SMAF – a functional profile) coupled with casemix management system (ISO-SMAF). Those with an SMAF score over 15 or an ISO-SMAF profile over 4 also received case management, individualised service plans, and a computerised clinical chart. Participants were assessed over 4 years for disabilities (SMAF), unmet needs, satisfaction with services, and empowerment. Information on utilisation of health and social services was collected by bimonthly telephone questionnaires. The main outcome measures were functional decline and hospital utilisation (ER and hospitalisation). Incidences of functional decline were not different between groups for the first 3 years but there were 137/1000 fewer cases in the intervention group in the 4th year (p&lt;0.001). Hospitalisations stabilised in the intervention group with no significant increase (p=0.578) over the 4 years, while control hospitalisations increased from 28%–37% (p=0.006). The difference in the pattern did not reach significance (p=0.113). No significant changes emerged for number of admissions, LOS, or readmission within either 30 or 90 days, or the proportion of participants consulting GPs or specialists annually. The proportion of participants who met with nurses was lower in the study group in years 3 (39% vs. 51%, p&lt;0.001) and 4 (32% vs. 62%, p&lt;0.001) than Tiered risk assessment system for the elderly</td>
<td>Canada</td>
<td>Jnl</td>
<td></td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>JHU ACG</td>
<td>2014</td>
<td>Use of ACG output to support practices participating in the unplanned admissions Directed Enhanced Service 2014–2015</td>
<td>NA – summary</td>
<td>Anecdotal</td>
<td>Unclear</td>
<td>A project implemented in GP practices in Leicester City, UK, uses ACG system to identify top 2% highest risk cohort over 18s in their practices so these can be case managed by means which include allocating each patient an accountable GP, co-producing with the patient a care plan and reviewing this care plan at regular intervals to prevent unplanned admissions. Practices had access to a specific report from the ACG grouper, which identified a high-risk cohort of their adult patients for inclusion in the case management register. In this way practices were identifying the highest risk patients in their practices using the ACG central system, rather than simply creating a subset drawn from their QOF (quality and outcome framework) registers. Claimed that the intervention is being funded by savings in hospital costs (e.g. reduced admissions), but no evidence provided.</td>
<td>ACG – commercial product claims</td>
<td>UK</td>
<td>Grey</td>
</tr>
<tr>
<td>JHU ACG</td>
<td>2014</td>
<td>Midlands and Lancashire Commissioning Support Unit – ACG case management report</td>
<td>NA – summary; expert opinion</td>
<td>Anecdotal</td>
<td>Unclear</td>
<td>Used ACG stratification with an integrated care, case management intervention. Claimed that the intervention was being funded by savings in hospital costs (e.g. reduced admissions). No statistics provided and the summary report was vague and prepared by the JHU ACG group itself, so no independent evaluation.</td>
<td>ACG –commercial product claims</td>
<td>UK</td>
<td>Grey</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------------</td>
<td>------</td>
<td>------------------------------------------------------------------------</td>
<td>-------------------------------------</td>
<td>----------------------</td>
<td>------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Leff B et al.</td>
<td>2009</td>
<td>Guided care and the cost of complex care: a preliminary report</td>
<td>Cluster RCT; guided vs. usual care</td>
<td>Supported practice</td>
<td>850 patients randomised to guided care: 446, or usual care: 404</td>
<td>See Boult et al. for a later paper. Used stratification based on those 65+ predicted to be at high risk of heavy health service utilisation using Hierarchical Condition Category model and randomised to guided care or control. Initial results concerning health service utilisation were more promising than those later reported by Boult et al. in the more recent paper on this study.</td>
<td>Integrated care intervention associated with risk stratification. See Boult entry</td>
<td>US</td>
<td>Jnl</td>
</tr>
<tr>
<td>Levine S et al.</td>
<td>2012</td>
<td>Home care program for patients at high risk of hospitalisation</td>
<td>RCT</td>
<td>Promising practice</td>
<td>156 intervention patients and 142 usual care controls</td>
<td>The objective was to assess the efficacy of a home care program designed to improve access to medical care for older adults with multiple chronic conditions who were at risk for hospitalisation as compared with usual care. Potential participants were identified from a pool of patients by using an electronic risk assessment screening process, which identified frail older adults at high risk for use of medical services by using an algorithm that considered variables such as age, sex, number of medications, number and types of chronic conditions, and use of EDs and inpatient hospital services. Home care program patients were less likely than usual care patients to be admitted to hospital during the 12 month intervention period (1 or more bed days 25.6% and 37.1%, respectively; P=.02). The intervention group reported significantly greater satisfaction with care than usual care recipients (t test=2.476; P=.014). There were no differences in terms of estimated costs of care between the groups. Authors queried the effectiveness of the risk stratification method used in identifying those requiring an integrated care intervention, but it was a local development tool for which validation data was not presented.</td>
<td>Integrated care intervention associated with risk stratification</td>
<td>US</td>
<td>Jnl</td>
</tr>
<tr>
<td>Lewis G et al.</td>
<td>2013</td>
<td>Impact on virtual wards on hospital use: a research study using propensity matched controls and</td>
<td>Control group design</td>
<td>Supported practice</td>
<td>intervention =989; matched controls=989</td>
<td>This study aimed to determine whether virtual wards have led to changes in rates of unplanned hospital admission compared to matched controls, and if so at what cost. The secondary aims were to assess the impact of the intervention on rates of A&amp;E attendance, social care provision, GP practice visits, and the use of community health services. Patients in Croydon, Wandsworth &amp; Devon virtual wards were compared to matched controls from national data. Compared with matched controls by area and individual characteristics, there was no evidence of a reduction in</td>
<td>Evaluation of virtual wards</td>
<td>UK</td>
<td></td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>-----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>McCall N et al.</td>
<td>2010</td>
<td>Evaluation of Medicare Care Management for High-Cost Beneficiaries (CMHCB) demonstration</td>
<td>Randomised community intervention trial</td>
<td>Supported practice – but report for government</td>
<td>6800 (split across 4 groups for analysis purposes – original, refresh, intervention and comparison)</td>
<td>Final report of the CMHCB with Massachusetts General Hospital and Massachusetts General Physicians Organization (MGH) – see Ferris et al. entry for further details. The principal objective of the CMHCB demonstration was to test a pay for performance contracting model and multicomponent case management intervention strategies for Medicare fee for service beneficiaries, who are high cost and/or who have complex chronic conditions. This randomised community control trial used demography (age, gender, race, Medicare status, residence), institutionalised status (previous stay in nursing home, long-term hospital care, skilled nursing facility etc.), Hierarchical Condition Category risk scores, health status (Charlson Index, comorbid condition, and ambulatory care sensitive conditions – ACSC), utilisation (number of acute hospitalisations, 90 day readmission, and ER visit including observation bed stays), expenditures, guideline concordance etc. MGH developed a series of clinical dashboards using data from its electronic medical record, claims data and enrolment tracking database. The dashboards allowed MGH to examine trends in health care utilisation and outcomes. Examples of dashboard indicators are: number of assessments completed within 90 days, number of referrals or interventions conducted, number of participants screened for depression etc. Includes the ‘refresh groups’ data when program was extended. The report presents findings suggesting improvement on most of the outcomes including acute care utilisation. It was successful reducing the rate of increase in acute care hospitalisations and ER visits but not 90</td>
<td></td>
<td>US</td>
<td>Grey – government report</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>-----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Optum</td>
<td>Internet – 2015</td>
<td>HealthNumerics-RISC – case study</td>
<td>Case study of practice application</td>
<td>Anecdotal – opinion</td>
<td>None provided</td>
<td>Cites North East Lincolnshire Integrated Care Program as a successful application of this risk stratification tool. Following risk identification by the tool, there was an integrated care intervention with social, community health and therapist teams, including intermediate care and acute care. Also tracked activity, interventions and outcomes during the intervention phase. Claimed that through reduced A&amp;E attendances and reduced inpatient stays it saved £1.7 million ($3.4 million) in first 9 months of application. Estimated a £3000 ($5900) saving per avoided ED admission. Commercial product claims – no independent evaluation or evidence.</td>
<td>Commercial product claims</td>
<td>UK</td>
<td>Grey</td>
</tr>
<tr>
<td>Roland M et al.</td>
<td>2012</td>
<td>Case management for at-risk elderly patients in the English integrated care pilots: observational study of staff</td>
<td>Observation study using surveys and analyses of secondary care utilisation</td>
<td>Promising practice</td>
<td>3646 patients &amp; 17,311 matched controls</td>
<td>The quantitative results from a multi-method evaluation of 6 of the UK integrated care demonstration projects which used risk profiling tools to identify older people at risk of emergency hospital admission, and combined this with intensive case management for people identified as at risk. The interventions focused mainly on delivery system redesign and improved clinical information systems. Most staff thought that care for their patients had improved. More patients reported having a care plan, but they found it significantly harder to see a doctor or nurse of their choice and felt less involved in decisions about their care.</td>
<td>UK integrated care demonstration projects</td>
<td>UK</td>
<td>Jnl</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Sonola L et al.</td>
<td>2013</td>
<td>South Devon and Torbay: proactive case management using the community virtual ward and the Devon Predictive Model</td>
<td>Case study of practice application</td>
<td>Other – system data, predictive model</td>
<td></td>
<td>The Devon Predictive Model (see Chenore above), based on primary and secondary care data, was used to identify the top 0.5% and 5% of patients at risk of ED admission in the following year for all GP practices. The patient lists are reviewed in the practice by a multidisciplinary team to select patients for proactive case management on a ‘virtual’ ward. These patients receive intensive assessment and care coordination to provide ongoing care and support in their home. Once their condition is stabilised, they are discharged from the virtual ward and receive usual care. Although there have been some reductions in hospital ED admissions for most regions since the introduction and use of predictive risk models (e.g. this drew attention to high-risk patients in the practice) and virtual wards, attribution to any particular intervention was less clear. Although there were reductions in ED admissions for 2010 and 2011 associated with virtual wards, this was not sustained in 2012, although virtual wards were not operating in all practices for all of the year. Torbay and South Devon have high virtual bed occupancy and have also reported a decline in residential placements as more patients remain at home. Evidence is suggestive at best and further longitudinal data are required. Implementation challenges were identified, which included change to governance arrangements during 2012. New privacy requirements were introduced in 2013 that affected the use of this predictive risk model in the shorter term.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literatur e type</td>
</tr>
<tr>
<td>-------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>-----------</td>
<td>---------</td>
<td>-------------------</td>
<td>--------</td>
<td>----------------</td>
</tr>
<tr>
<td>Stewart MJ et al.</td>
<td>2013</td>
<td>Successfully integrating aged care services: a review of the evidence and tools emerging from a long-term care program</td>
<td>Literature review</td>
<td>Promising practice</td>
<td>Found 45 articles and 2 books authored/co-authored by PRISMA team. Also found 20 articles not authored by PRISMA team</td>
<td>PRISMA review – this application lessened functional decline, significantly reduced admissions following an ED visit, reduced GP visits and reduced costs. General process: prior to project entry, clients were screened for risk of functional decline using PRISMA-7. This was done by single entry point staff, or opportunistically by health care professionals who would onward refer (Hebert et al. 2008). Those deemed at risk of decline were then assessed with the SMAF and assigned an ISO-SMAF profile. A local case manager used the ISO-SMAF profile to coordinate care and resources. There was a reduction in both the incidence and prevalence of ‘functional decline’ among patients exposed to the PRISMA intervention, with a lower annual incidence of functional decline of 137 cases per 1000 individuals in the PRISMA group (Hebert et al. 2010). The program also demonstrated a progressive reduction in handicap levels (Hebert et al. 2008), decreased prevalence of unmet needs for those living in the community (Dubuc 2011, Hebert et al. 2010), and clients reported significantly improved feelings of satisfaction (p&lt;0.001) (Hebert et al. 2008) and empowerment (p&lt;0.001) (Hebert et al. 2010). The proportion of clients in the PRISMA group consulting with a medical specialist once a year dropped from 60% to 50% (p&lt;0.001). The comparative groups remained steady at 60% (Hebert et al. 2008). There was no demonstrated difference in rates of hospitalisations, LOS, or readmissions, or in use of home care or volunteer services (Hebert et al. 2008). Desire for institutionalisation was reduced in the first 2 years of the study but not in the overall 4 years of the study (Hebert et al. 2008). Intervention subjects had fewer nurse and other HP consults compared to controls in years 3 (p&lt;0.001) and 4 (p&lt;0.001) of the study. Those in study group were more likely to be admitted after a visit to ED compared to controls (p=0.043), possibly due to intervention subjects only going to ED for serious conditions (Hebert et al. 2010). Economic benefits showed that for intervention subjects costs reduced, while costs rose for control subjects (p=0.001) (Hebert et al. 2008). Intervention and control subjects both experienced a drop in annual consultation costs, but the intervention group drop was much</td>
<td>Review of PRISMA</td>
<td>Canada</td>
<td>Jnl</td>
</tr>
</tbody>
</table>
Table 1. \textit{A Victorian government initiative, HARP, based on KP risk stratification approach was designed to identify those at risk of repeated hospitalisation at the time of ED presentation or hospital admission or at discharge from hospital in order to target alternative interventions. The evaluation methodology included (i) descriptive analysis of outcomes for individual projects, groups of projects, and the overall hospital system, (ii) comparative analysis of individuals before and after enrolment in selected HARP projects, (iii) some comparative analysis between a selection of HARP and non-HARP patient cohorts. The key HARP outcomes were number of ED presentations, unplanned hospital admissions, and LOS in case of an unplanned admission episode. In general, HARP intervention patients demonstrated 35\% fewer ED presentations, 52\% fewer ED admissions and 41\% fewer days in hospital (P<0.05) when compared with non-HARP patients, but only summary data are presented with limited statistical analysis. HARP had a positive overall impact on the level of hospital utilisation in Victoria. Note: details about the HARP evaluation methodology need to be examined to see the possibility of regression to the mean effect. Evaluation guide available at www.health.vic.gov.au/harp-cdm/harp_eval_guide.pdf but it was not accessible. It appears this model requires validation.}

<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Victoriaan Govt Dept Human Services</td>
<td>2006</td>
<td>Improving care Hospital Admission Risk Program (HARP)</td>
<td>Government report</td>
<td>Other–multiple methodologie s (see Column G)</td>
<td>Unclear</td>
<td>A Victorian government initiative, HARP, based on KP risk stratification approach was designed to identify those at risk of repeated hospitalisation at the time of ED presentation or hospital admission or at discharge from hospital in order to target alternative interventions. The evaluation methodology included (i) descriptive analysis of outcomes for individual projects, groups of projects, and the overall hospital system, (ii) comparative analysis of individuals before and after enrolment in selected HARP projects, (iii) some comparative analysis between a selection of HARP and non-HARP patient cohorts. The key HARP outcomes were number of ED presentations, unplanned hospital admissions, and LOS in case of an unplanned admission episode. In general, HARP intervention patients demonstrated 35% fewer ED presentations, 52% fewer ED admissions and 41% fewer days in hospital (P&lt;0.05) when compared with non-HARP patients, but only summary data are presented with limited statistical analysis. HARP had a positive overall impact on the level of hospital utilisation in Victoria. Note: details about the HARP evaluation methodology need to be examined to see the possibility of regression to the mean effect. Evaluation guide available at <a href="http://www.health.vic.gov.au/harp-cdm/harp_eval_guide.pdf">www.health.vic.gov.au/harp-cdm/harp_eval_guide.pdf</a> but it was not accessible. It appears this model requires validation.</td>
<td>HARP readmissions model</td>
<td>Australia</td>
<td>Grey</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Dixon J et al.</td>
<td>2004</td>
<td>Can the NHS learn from US managed care organisations?</td>
<td>Semi-structured interviews</td>
<td>Emerging practice</td>
<td>NA</td>
<td>Study which reviewed staff of 5 managed care organisations in the US (see Light 2004) to identify lessons to be learnt by NHS. Summary points that may explain the better performance of managed care organisations such as KP in key outcomes (admissions, bed days): competitive pressures between managed care organisations provide an incentive for innovation in management of chronic diseases; doctors in these organisations had a strong management role; goals were agreed between clinicians and managers, and financial incentives existed to improve care; all managed care organisations identified high-risk patients and targeted intensive nurse led outreach care to minimise hospital admissions; multifaceted chronic disease management programs were used, in which self-care and patient education were central features.</td>
<td>Relates to NHS and US managed care comparisons</td>
<td>UK</td>
<td>Jnl</td>
</tr>
<tr>
<td>Lewis G</td>
<td>2015</td>
<td>Next steps for risk stratification in NHS</td>
<td>Government report</td>
<td>Expert opinion</td>
<td>NA</td>
<td>The predictive accuracy of many risk stratification tools is modest and one needs to consider the adverse effects of false positive and false negative results, as well as the benefits of true positive and true negative results. Although the risk threshold can be varied to examine the cost implications, the benefits of the model must outweigh the costs. Some strategies to improve the impact of risk stratification such as impactibility could potentially worsen health inequalities if applied inappropriately. Many of the interventions offered in risk stratification programs appear to increase cost. As there is a lack of robust evidence to support hospital avoidance programs, further research is required.</td>
<td></td>
<td>UK</td>
<td>Grey – government report</td>
</tr>
<tr>
<td>Light D</td>
<td>2004</td>
<td>Making the NHS more like Kaiser Permanente</td>
<td>Discussion</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Refers to w studies, Feachem et al. (2002) and Ham et al. (2002), which indicated that admissions and hospital bed days for KP North California were less than half that for a comparable population in the NHS (notes some issues with the Feachem study). Refers to Dixon et al. (2004) study, which reviewed 5 managed care organisations in the US. Summary points that may explain the differences: current financial and organisational structures militate against true integration; doctors from primary, secondary, and tertiary care should be given joint responsibility for managing</td>
<td>Relates to NHS and US managed care comparisons</td>
<td>UK</td>
<td>Jnl</td>
</tr>
</tbody>
</table>
clinical services; commissioning of health services needs to become less hospital centred.

<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>NHS England</td>
<td>2015</td>
<td>NHS England: using case finding &amp; risk stratification</td>
<td>Government report</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Useful UK report for explaining difficult statistical concepts about risk stratification to a broader audience. Uses of risk stratification for case finding included identifying those with chronic conditions or complex multi-morbidity who may benefit from case management and care planning; to reduce ED admissions; to identify and target specific service needs of particular patient groups (e.g. diabetes); to identify suitable patients for caseloads of specialist nursing or medical services and for end of life advance care planning, or to reduce avoidable unplanned admissions. Other uses might include planning to address other identified service utilisation issues, establishing capitated budgets, to inform fund distribution and to consider the inclusion of social care data and social risk factors in risk engines to predict outcomes such as hospital admission or admission to a permanent care home. Noted the need for the increased identification of frailty in the absence of multi-morbidity. Identified issues for selection of risk management tools. Discussed case studies successfully using risk stratification for population profiling in the UK which are relevant to planning, resource and cost issues, but these did not include an evaluation of the outcomes of risk stratification interventions.</td>
<td>Uses of risk stratification for case finding. Advantages of a population profiling approach</td>
<td>UK</td>
<td>Grey - government report</td>
</tr>
</tbody>
</table>

<p>| Purdy S et al. | 2010 | Avoiding hospital admissions: what does the research evidence say? | Rapid review | Promising practice | Unclear but largely based on review articles | Reasonably comprehensive but rapid review of risk factors for avoidable ED hospitalisation and the effectiveness of associated intervention as at 2010. Notes evidence for social deprivation and continuity of GP care as important predictors. Notes risk tools included simple questionnaires (e.g. EARLI) as well as computer based models with no clear advantage of using one tool vs. another. Cites evidence that integrating health and social care and primary and secondary care may reduce admissions. Telemedicine | Rapid review of integrated care interventions | UK | Grey – King’s Fund report |</p>
<table>
<thead>
<tr>
<th>First author</th>
<th>Year</th>
<th>Topic</th>
<th>Study design</th>
<th>Strength of evidence</th>
<th>Study nos.</th>
<th>Summary</th>
<th>Additional comment</th>
<th>Country</th>
<th>Literature type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roland M &amp; Abel G</td>
<td>2012</td>
<td>Reducing emergency admissions: are we on the right track?</td>
<td>Discussion article</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Cautions against the current focus on only those at high risk or ‘frequent flyers’, as overall these groups only account for a small per cent of admissions compared to the rest of the population. Thus it is likely that more broadly based population intervention strategies may have a greater impact. Cautions about ignoring factors such as supply induced demand. Identifies the need to consider regression to the mean effects by having an appropriate control group or comparison group or data. Identifies the need to</td>
<td>Raises topical issues</td>
<td>UK</td>
<td>Jnl</td>
</tr>
<tr>
<td>First author</td>
<td>Year</td>
<td>Topic</td>
<td>Study design</td>
<td>Strength of evidence</td>
<td>Study nos.</td>
<td>Summary</td>
<td>Additional comment</td>
<td>Country</td>
<td>Literature type</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>-------</td>
<td>--------------</td>
<td>----------------------</td>
<td>------------</td>
<td>---------</td>
<td>-------------------</td>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Roland M</td>
<td>2012</td>
<td>Reducing emergency admissions: are we on the right track?</td>
<td>Presentation</td>
<td>Expert opinion</td>
<td>NA</td>
<td>Slide presentation on the above paper, but also includes a succinct summary of the Purdy et al. (2012) review of integrated care interventions.</td>
<td>As above</td>
<td>UK</td>
<td>Grey</td>
</tr>
</tbody>
</table>

consider random variation in reporting outcome figures based on small samples. They also note that one should not assume there is a correct rate of admission or referral to hospital or assume that fewer admissions or referrals are necessarily better – clinical audit will be required to make these figures meaningful and identify the problems in care.