bureau of health information

Technical report

Using predictive risk modelling for performance measurement

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State Health Publication Number: (BHI) 170688
ISBN: 978-1-76000-776-8

Suggested citation:
Bureau of Health Information. *Using predictive risk modelling for performance measurement.* Sydney (NSW): BHI, 2018.

Please note there is the potential for minor revisions of data in this report.
Please check the online version at **bhi.nsw.gov.au** for any amendments.

Published March 2018

Table of contents

Foreword 2

Summary 3

Setting the scene 5

- About this report 7
- Data and methods 9

Section 1: Defining and validating measures 11

- Defining the cohort 13
- Identifying events of interest 15
- Modelling: Risk score thresholds 17
- Modelling: Risk factors and data linkage 19

Section 2: Applying predictive risk modelling (PRM) to performance assessment for 30-day readmissions to hospital 21

- Hospital readmissions: Local health district performance 23
- Stratifying risk 25

Appendices 30

References 35

Acknowledgements 37

Foreword

Advances in statistical modelling in the past 30 years have revolutionised science. Exponential growth in computing capacity has meant widespread analyses of huge datasets are possible and associations between a wide range of variables and outcomes of interest can be explored. Predictive modelling is now a core tool in investigations across disciplines as diverse as climate science, financial planning, and infrastructure development.

In health, predictive modelling has been used to identify in real time those patients who are at high risk of needing extensive support and healthcare services in the future – often referred to as case finding. Predictive modelling has also been used to evaluate programs and to assess performance – comparing expected outcomes with observed. However to date these approaches have not been well integrated. This report explores whether performance can be assessed using the relative performance of providers in altering patient trajectories within different risk strata.

Quantifying risk and identifying success in mitigating and managing risk proffers considerable opportunities to improve patient experiences and outcomes as well as value for money in healthcare systems.

The work featured in this report was led by the 2016 Commonwealth Fund Australian-American Health Policy Fellow, Dr Tracy Johnson. It was a privilege for the Bureau of Health Information (BHI) to act as the host organisation for the fellowship year. The staff at BHI learned a huge amount from Tracy and gained real insight into healthcare provision in the US. More broadly, Tracy was unstintingly generous in her engagement and advice; and her year with us also benefited state and federal Ministries of Health, academic partners, and research and improvement organisations.

The fellowship year reinforced for us all that building communities of practice brings considerable benefits to performance measurement endeavours. These benefits range from the technical, in terms of analytic guidance and idea generation, to the collegial, in terms of forging supportive and productive professional partnerships.

Dr Kim Sutherland
Former Senior Director, Performance Measurement and Reporting, Bureau of Health Information

Summary

Using predictive risk modelling for performance measurement presents key issues to consider when building a predictive risk model (PRM). It explains important concepts about PRMs and applies those concepts to groups of patients at risk of hospitalisation in NSW. It demonstrates how predicting the risk of admission is influenced by the choice of:

- dataset
- study group or cohort
- modelling strategy.

The examples throughout the report illustrate the impact of these choices on analytic efforts to segment and describe high-risk populations, assess health system performance and track risk-stratified events over time.

The report outlines the development and application of PRMs in different patient populations to estimate the probability of distal (one-year hospitalisation) and proximal (30-day readmission) outcomes. These outcome probabilities were then used to define high-, medium- and low-risk groups.

An existing statistical model developed by the Bureau of Health Information (BHI) was used to predict 30-day readmission rates among patients who were initially admitted for congestive (chronic) heart failure (CHF) and to assess local health district (LHD) level performance in rates of 30-day readmission while adjusting for patient case mix. For each LHD, the predicted probabilities of readmission were stratified to identify high-risk populations and compare LHD performance within each risk stratum.

Study cohort selection

For any approach that seeks to predict utilisation or patient need, a clearly defined cohort is required. For example, is the population of interest all adults? All adults over 65 years of age? All who were hospitalised? All with a particular set of comorbidities?

Using data from the Sax Institute's 45 and Up Study, different analyses explored how the composition of study populations influenced results. Five study cohorts were defined by varying each study's parameters, including: the combination of data sources, the length of the prediction period and the size of the group. Changing the criteria for cohort selection shaped the study populations' risk profiles and had implications when applying a PRM to different study cohorts.

Defining and capturing events of interest

This report adopts an approach similar to that used by the NSW Health Chronic Disease Management program, incorporating multiple predictive factors in a model, and then using the output to identify groups at high risk of hospitalisation.

The 45 and Up Study was used to understand how changes in the definition of prediction periods influenced the number of hospital admissions captured in the analysis. Particular attention was paid to the effects of regression to the mean and its potential to overestimate the risk of an admission.

Making predictions

A single dataset rarely contains all of the variables that are predictive of the event of interest. When available, linking datasets can improve prediction accuracy by including more information in the model (for example: age, sex, comorbidities and geographic location). Data from hospital records, the Registry of Births, Deaths and Marriages (RBDM), the Medicare Benefits Schedule (MBS) and the Pharmaceuticals Benefits Scheme (PBS) were linked to the 45 and Up Study.

Sensitivity analyses highlighted the impact that adding information to a model had on the percentage of the study population classified in high-risk categories. They also showed that as the definition of high-risk is made more stringent, the high-risk group becomes more concentrated with people with complex health needs.

Predictive risk models are not one-size-fits-all. Seemingly small changes in inclusion and exclusion criteria, or in modelling decisions, can profoundly affect predictions generated by the model. Greater awareness and transparency about the impact of modelling decisions informs both analysis and subsequent action to improve care.

Performance attribution: Applying PRM to performance measurement

Statistical models can assess the relative risk of patient outcomes, where risk is estimated by patterns in a study population. While controlling for relevant predictive factors, if a patient does significantly better or worse than the expected outcomes, this can be attributed to the performance of providers in altering the expected trajectory.

After running a statistical model previously developed by BHI, the predicted probabilities of 30-day CHF readmission to hospital were stratified by quintiles in order to observe variability between LHDs. The objective was to compare, within risk strata, each LHD's observed and expected performance. For some LHDs, observed performance was better than expected for higher-risk patients.

These analyses contribute to a larger body of work by BHI that focuses on developing outcome and process indicators to measure the performance of the public healthcare system in NSW.

Setting the scene

Patients' health status can change over time in ways that range from the subtle to the conspicuous. Health status is influenced by changes in risk profiles, which in turn are affected by genetics, lifestyle, behaviours, and wider social and environmental factors. Together, health status and risk profile influence how patients seek healthcare and interact with service providers.[1,2]

The need to understand the nature of patient risk has accelerated as reducing rates of unplanned readmission to hospital has emerged as an international policy goal and common performance metric.[3,4,5] Considerable efforts are underway in healthcare systems to optimise the organisation and financing of hospital, primary care and ancillary services for individuals with complex needs who are at risk of hospitalisation.[6,7,8,9,10,11,12]

This section provides some context for the report and outlines data and methods used in its production.

About this report

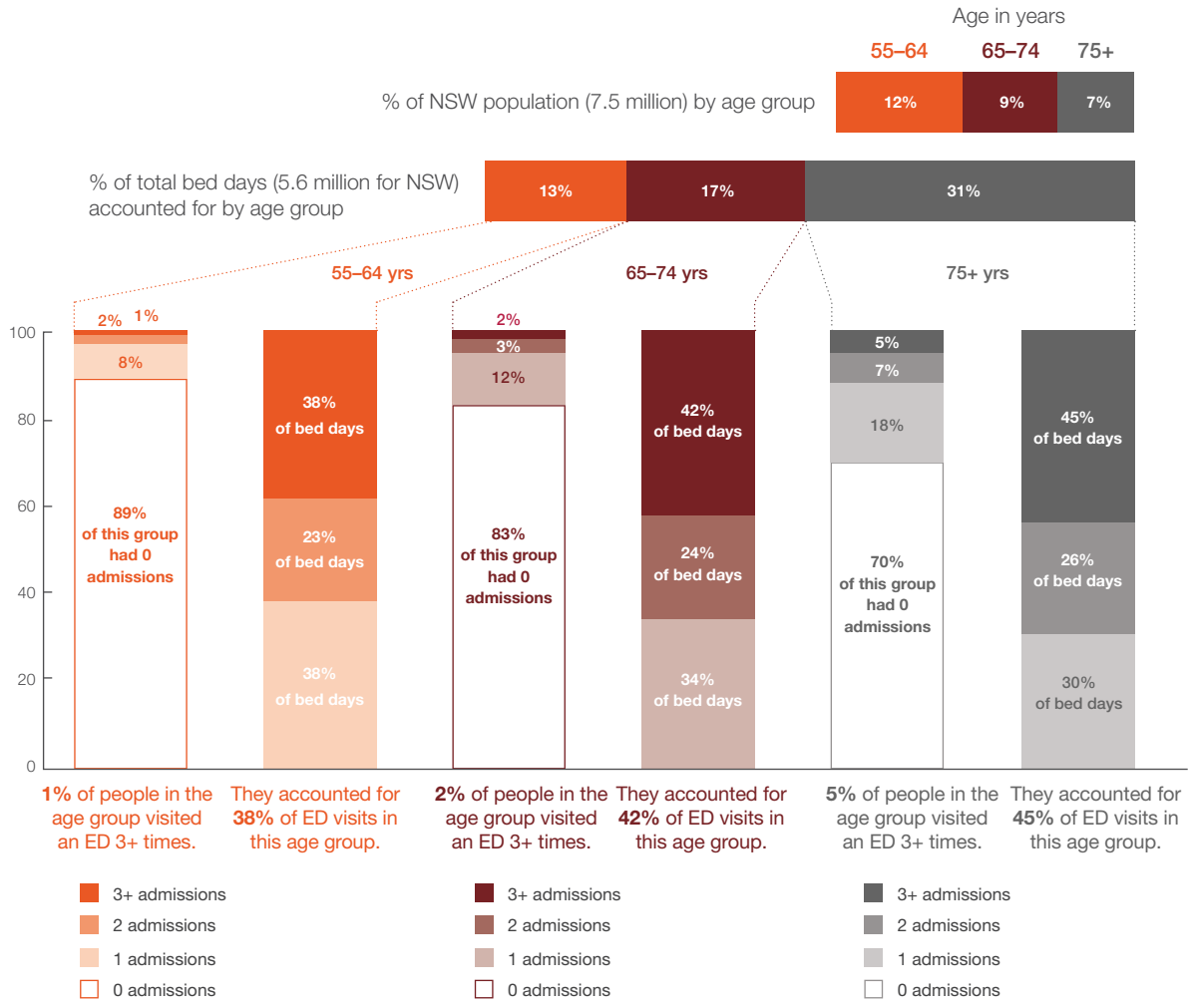
Background

In NSW, a small percentage of the adult population accounts for a large share of total hospitalisations, readmissions, and overall health expenditure. Between July 2013 and June 2014, in the 55–64 year old age group, 1% of people accounted for 38% of all hospitalisations (Figure 1). These high-users are often the focus of concerted efforts to improve the integration of care across providers and sectors; seeking to minimise the need for hospitalisation.[13]

Classifying patient populations in terms of risk profiles provides a number of analytic and clinical opportunities. It can:

- inform real time clinical decision-making
- identify patients who are likely to be high users of health care services in the future
- compare how different providers manage patients with various risk profiles.[14, 15]

Figure 1 Utilisation of acute overnight hospital care (public and private hospitals) by age group, NSW, 2013–2014



What is a predictive risk model (PRM)?

A PRM is a mathematical model in which an event, in this case a hospitalisation, is expressed as a function of factors that predict the occurrence of that event.

Various types of PRMs are built for different purposes. Two common applications of PRMs are case finding patients at high risk of an event and assessing health system performance.

Case-finding seeks to identify patients who are good candidates for enrolment in a risk-management program or require more intensive care. Ultimately, the aim is to deliver appropriate services for the level of need. Additionally, PRMs can be used to examine variation in provider performance, particularly for outcomes amenable to intervention.

For performance applications, hospital-level factors are excluded from the model to avoid adjusting for variation that is a result of the care that was provided. Case-finding models, in contrast, may include system-level factors because the interest is in the patient's risk of the event as opposed to assessing institutional performance.

Structure of this report

This report establishes a rationale for, and general approaches to, assessing patient risk. It reviews the PRM literature and identifies the main uses of PRMs while contrasting the priorities and needs of various applications. It has two main sections:

Section 1 outlines methodological considerations in assessing the use of different data sources and models to build a PRM. It presents several alternative approaches for specifying PRMs to segment high-risk populations and events. It presents issues researchers should consider when model-building.

Section 2 presents an application of a PRM for the purposes of performance measurement, looking at 30-day readmissions in a cohort of patients with CHF in NSW. Using the model output, LHD performance within different risk strata are presented.

Specifically, a PRM that was previously developed by BHI is used to assess LHD variation in 30-day readmission among patients with an index hospitalisation for CHF. This model was defined with the intention of measuring hospital performance. For this reason it includes only patient-level characteristics that are non-modifiable by the health system such as age, sex and comorbidities.

Data and methods

Data sources

This report draws on two main linked data sources. The first is based on the NSW 45 and Up Study where survey responses are linked to administrative data records. The second is based on linked administrative data only.

45 and Up Study

The analyses described in Section 1 of this report used data collected by the 45 and Up Study (www.saxinstitute.org.au). The 45 and Up Study is managed by the Sax Institute in partnership with Cancer Council NSW and other partners: The National Heart Foundation of Australia (NSW Division); NSW Ministry of Health; NSW Government Family & Community Services; the Disability Council NSW; and the Australian Red Cross Blood Service. We thank the many thousands of people participating in the 45 and Up Study.

Participants were randomly sampled from the Department of Human Services (DHS, formerly Medicare Australia) enrolment database, which provides near complete coverage of the population of NSW. People over 80 years of age and residents of rural and remote areas were oversampled. A total of 266,942 participants from NSW, Australia, aged 45 and years and over, joined the study by completing a baseline questionnaire between January 2006 and December 2009, and giving signed consent for follow-up and linkage of their information to routine health databases. Approximately 18% of those invited responded to the survey – this represents about 11% of the population in NSW aged 45 years and older.[16]

After obtaining patient consent, data were obtained from administrative health databases and linked to participants' survey responses. The administrative data included public and private sector hospital discharges and ED presentation information from the NSW admitted patient and emergency department data collections (APDC and EDDC, respectively).

Data from general practitioner (GP) care and prescription drug use were obtained from the MBS and the PBS, supplied by the Australian Department of Human Services. Date of death information was obtained from the RBDM.

The Sax Institute used a unique identifier provided from the DHS to link survey responses to MBS and PBS data. The Centre for Health Record Linkage (CHeReL) conducted the data linkage of the APDC, EDDC and RBDM to the survey data using probabilistic methods. Quality assurance tests show false-positive and false-negative rates for probabilistic data linkage of 0.4% and <0.1%, respectively.[17]

The 45 and Up Study was approved by the University of NSW Human Research Ethics Committee (HREC). Approval to conduct the analyses presented in this report was granted by the NSW Population and Health Services Research Ethics Committee (HREC/15/CIPHS/42, 04/10/16).

Respondents to the 45 and Up Study consented to having their answers linked to other data sources such as hospital, pharmaceutical, GP and mortality records. The data linkages enabled simulation of a range of decisions in choosing cohorts and variables. In separate analyses the definition of events of interest, models and risk categories were changed to see how this affected the composition of study groups and the results of the analyses.

Health Information Exchange and RBDM

A series of analyses that focused on 30-day readmissions among CHF patients drew on hospitalisation data from the NSW Ministry of Health's Health Information Exchange (HIE), linked to the RBDM. Probabilistic linkage was performed by CHeReL. Access to the data was provided through the Secure Analytics for Population Health Research and Intelligence (SAPHaRI) data warehouse.[18]

Methodological considerations

Regression to the mean

Studies show that many high-risk patients are intermittently high risk rather than being persistently so. It is not unusual for a year with a high number of hospitalisations to be followed by a year with far fewer. Focusing on patients who experience a large number of successive hospitalisations tends to identify those at peak service use who are towards the end of an exacerbation period. Predicting future adverse events based on this identification strategy can bias results. This refers to a statistical concept known as 'regression to the mean': if an extreme measure is captured the first time, it is statistically less likely that the next measure will be as extreme.[19]

Regression to the mean can exaggerate the effects of health improvements and misguide resource allocation if high-users are over-represented in the study population. Some applications of PRMs seek to avoid this problem by identifying patients earlier, with the aim of preventing these exacerbation periods.

Statistical model

The outcome of interest in a PRM is typically whether the patient experienced the event or not. Logistic regression is an appropriate model for handling binary outcome variables.

Risk adjustment is important when making performance comparisons between providers. Certain patient factors influence the probability of a readmission regardless of the quality of care received during the index admission. Providers who treat sicker patients are not expected to achieve the same results as those who treat healthier patients. Different approaches were used to capture whether patients were sicker – either self-rated health for the 45 and Up studies, or the Elixhauser comorbidity index for the HIE-based analyses.

Further information on modelling strategies has been published previously by BHI.[20]

Analyses were conducted in SAS 9.3 and Stata 12.[21,22]

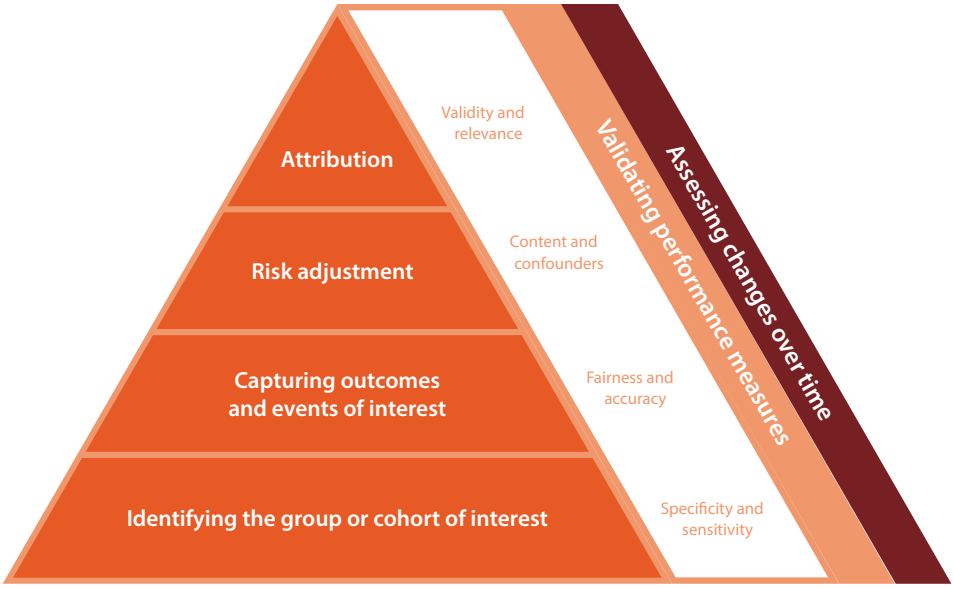
Section 1: Defining and validating measures

This section aligns with the Bureau of Health Information's framework for performance measure development (Figure 2). It focuses on four key analytic questions:

1. **How should the cohort be defined?** Analyses consider options for patient groups based on inclusion and exclusion criteria, and data availability.
2. **What events or outcomes should be measured?** Outcomes can be patient-based (for example, among those with comorbidities) or service-based (for example, among all hospitalisations). The outcome can be a single event (an admission to hospital) or a pattern of events (three admissions within a six month period). Ultimately, PRMs aim to derive the predicted risk of an outcome that is amenable to interventions.
3. **How can fair comparisons be made?** The inclusion and exclusion of different predictor variables in a statistical model are assessed to determine their influence on which patients or events are classified as high-risk and for what duration of time. An important consideration related to this is regression to the mean, particularly for patients who experience a large number of successive hospitalisations.
4. **Who should performance be attributed to?** In developing PRMs, consideration is given to modifiable and non-modifiable elements of risk and where any unwarranted variation in risk realisation or mitigation can be attributed.

The PRMs presented in this report are the result of extensive exploratory analyses. Stakeholder feedback from the NSW Ministry of Health, clinicians and predictive modelling experts was also sought to identify the scope of reporting and the key considerations to take into account when interpreting results.

Figure 2 The Bureau of Health Information's framework for performance measure development



Defining the cohort

With predictive risk analyses, the definition of the study cohort addresses issues of scope. Is the primary field of interest all people living in a defined area? Only those with chronic health conditions? Only those aged over 65 years? Only those with at least one hospitalisation in the course of a year? It also addresses issues of data access – how can research questions be operationalised given data availability?

Within a study cohort, the outcome of interest can be defined so that an individual may be counted once only or more than once. Governments or health funds often track per capita spending and tend to conceptualise risk as an inherent characteristic of a person (for example, a patient's profile suggests an elevated risk of unplanned hospital admissions). In this type of analysis, an individual can only be counted once. Conversely, risk may be viewed as attaching to an event, service or pattern of utilisation (for example, discharges that are at higher risk of an unplanned readmission). In these event-based analyses, individuals can be counted more than once if they experienced multiple events within the selection period.

Study cohorts and design

The implications of varying inclusion and exclusion criteria were explored using the SAX Institute's 45 and Up Study data in five distinct studies. The studies demonstrate how assumptions about the nature of risk are operationalised. All five studies use a person-level design and conceptualise risk as an individual characteristic. They vary in the length of study period and the data sources used to build the cohorts (Figure 3).

Study 1 and Study 2 include survey respondents who had at least one hospital admission during a 12-month study inclusion period (2008–2009). For Study 3, the inclusion period was extended to three years (2006–2009). Using the same inclusion period, Study 4 added respondents who attended an ED and Study 5 added respondents who had an MBS or PBS record.

Figure 3 Study definitions and inclusion and exclusion criteria

Measure	Study description	Time range for inclusion	Index event	Prediction time range	Data sources*	Cohort size	Age
Study 1	Discharged from hospital in preceding 12 months	2008-2009	Yes (hospital discharge)	One-year following index admission	45 and Up Study, APDC, RBDM	69,388	45+ years at index admission
Study 2	Discharged from hospital in preceding 12 months	2008-2009	No	2009-2010	45 and Up Study, APDC, RBDM	69,395	45+ years on 30 July 2009
Study 3	Discharged from hospital in preceding 3 years	2006-2009	No	2009-2010	45 and Up Study, APDC, RBDM	134,438	45+ years on 30 July 2009
Study 4	Discharged from hospital or used ED in last 3 years	2006-2009	No	2009-2010	45 and Up Study, APDC, EDDC, RBDM	154,724	45+ years on 30 July 2009
Study 5	Discharged from hospital or used ED, primary care or pharmacy in last 3 years	2006-2009	No	2009-2010	45&Up, APDC, EDDC, MBS, PBS, RBDM	263,328	45+ years on 30 July 2009

* Dataset abbreviations refer to: Admitted Patient Data Collection (APDC), Emergency Department Data Collection (EDDC), Medicare Benefits Schedule (MBS), Pharmaceuticals Benefits Scheme (PBS) and Registry of Births, Deaths and Marriages (RBDM)

Studies 1–4 defined populations that would be similar to those drawn exclusively from hospital admission and emergency department (ED) attendance data. Study 5 is most similar to a population-based design, since most survey respondents used hospital, ED, primary care or pharmacy services between 2006 and 2009 (only 327 out of 263,655 did not use at least one of these services).

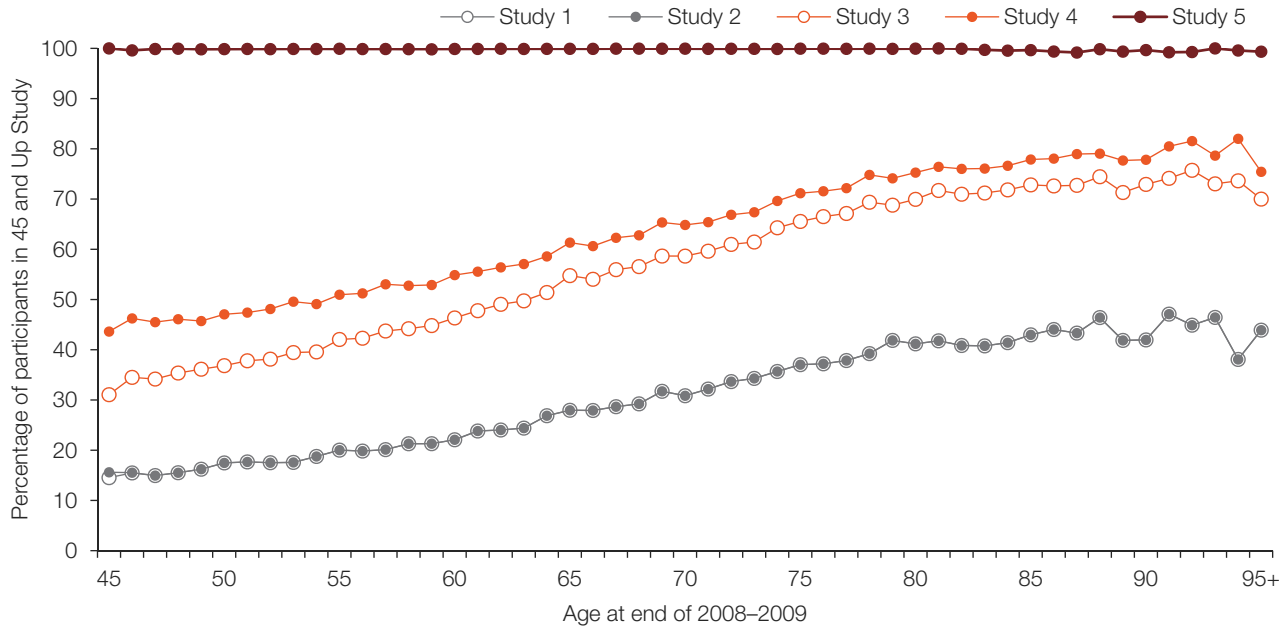
Event capture was based on the date of discharge for hospital admissions, the date of presentation for ED attendances, and the date of service for MBS and PBS data. All studies excluded respondents who died before the start of the prediction period.

Study inclusion criteria, respondent age and data source

For each study, inclusion criteria varied in their impact across one-year age bands. For example, while almost all respondents were included in Study 5 regardless of age group, Study 1 included only 31% of the 45 and Up Study respondents who were aged 70, whereas Study 4 included 65% of 70-year-old respondents. As respondent age increased in Studies 1-4, the likelihood that respondents met the inclusion criteria also increased (Figure 4).

The relative position of the age-based inclusion lines in Figure 4 is dictated in large part by the data source. Any study based on hospital admissions data will contain a higher percentage of seriously ill individuals compared with the general population, so the collective risk of a subsequent emergency admission will also be much higher. Conversely, when the general population is used as the basis of a study, the risk of a subsequent emergency admission decreases since inclusion is not predicated on health service use. Identifying these study selection factors is important for interpreting PRMs and applying them to different contexts.

Figure 4 Percentage of survey respondents in the 45 and Up Study included in each study, by age



Identifying events of interest

Determining the risk of an event typically requires decisions about the definition of the outcome, and the prediction period for the occurrence of that outcome. The prediction period can broadly be understood as being either event-triggered (for example, a readmission within 30 days of discharge) or time-dependent (for example, forecasting whether an outcome will happen in a particular time interval).

In Figure 5, the outcome is an emergency admission to hospital at any time within the 24 months after study entry (prediction period). For Study 1, the outcome is event-triggered, and the prediction period starts at the end of the index admission. For the other studies, the outcome is time-dependent, and the prediction period starts at the end of the selection period i.e. 1 July 2009.

Figure 5 shows the observed admission rates per month for each study in the 24 months following selection. The figure shows the variation in the admission rate between study groups; as the proportion of people in a study with a recent hospital admission decreases, the admission rate also decreases. Studies 1 and 2 consist of patients with a hospital admission in the selection period, and had the highest admission rates in the subsequent 24-month period. Study 5 includes people who did not have a hospital admission or an ED presentation between 2006 and 2009; it resembles most a sample from the general population. It also had the lowest admission rates in the subsequent 24 months.

Figure 5 also shows the phenomenon commonly referred to as regression to the mean. Focusing on patients who experience a large number of successive hospitalisations tends to identify those at peak service use who are nearing the end of an exacerbation period. Regression to the mean can exaggerate the effects of improvement interventions and misguide resource allocation if the study population is over-represented by those who experience extreme events.

Regression to the mean is most marked for Study 1, where people were selected using index admission. Although the members of Studies 1 and 2 are almost the same, the starting times for the prediction period differ, and there were more admissions in the first months after study selection for the event-triggered Study 1. This difference decreased over time.

Study inclusion criteria can impact the probability of events since the distribution of risk will be influenced by the underlying population.

Notably, hospital admissions are subject to seasonal variation. Seasonality is of greater concern if the prediction period is time-dependent rather than event-triggered. Causes of seasonality can include regular events such as low admissions for elective surgery in December and January, and occasional events such as high admissions during an influenza outbreak. For Studies 2–5, which were time-dependent, admissions show some seasonality whereas there was no discernible seasonality seen in Study 1.

Defining the model

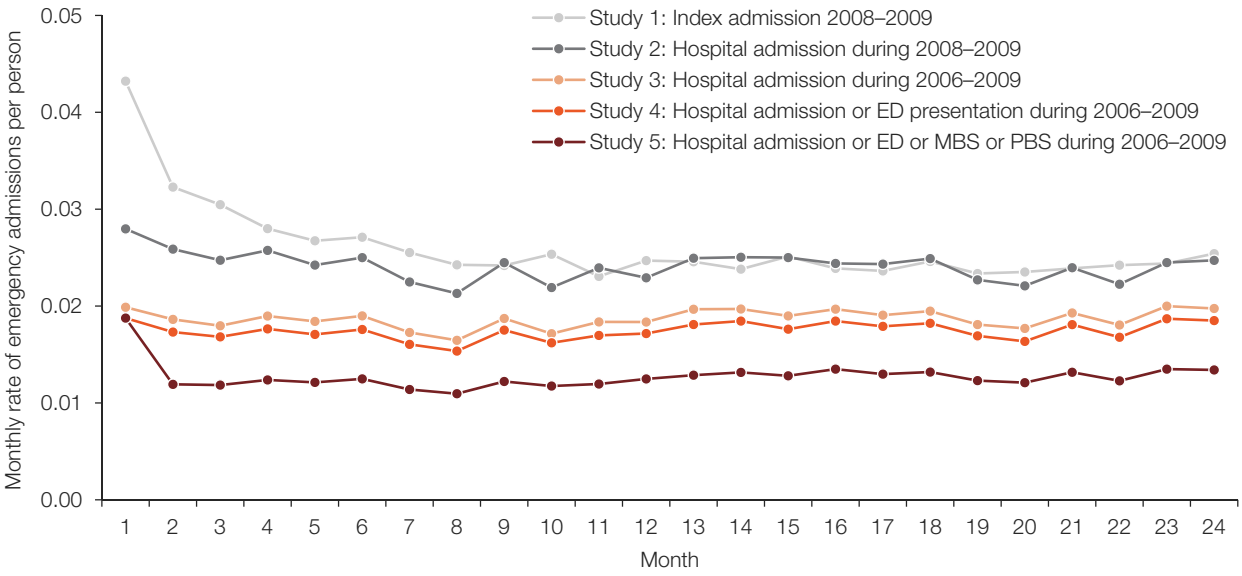
Methods for defining and fitting a statistical model affect the predicted risk and the composition of risk groups.

The statistical models in Studies 1–5 were based on the Hospital Admission Risk Prediction (HARP) tool developed in Ontario, Canada with a particular interest in the effect of decisions on the composition of risk groups.[5] A dichotomous outcome variable was defined to indicate whether the person had an emergency admission during the 12-month prediction period. The variables used are listed in Appendix 1.

Dataset linkage increases the options for variable inclusion. Linkage can improve model performance by allowing more variables to be used for study group selection and for prediction. In Study 5, patient selection was based on data that were linked across hospital and non-hospital settings. For the other studies, patient selection was based on hospitalisation data only.

In some circumstances, particularly where predictive analyses are used to inform practice or assess performance, studies divide the available data into two parts: one for model development and the other for model verification.[20] In this report, the focus is on the effect of varying definitions of PRM, so all data were included in the analysis.

Figure 5 Monthly admission rates over 24 months following study entry



Modelling: Risk score thresholds

A number of technical modelling specifications – outcome selection, prediction periods and risk thresholds – can influence which patients are deemed high-risk. Attention to these modelling details helps ensure the meaningfulness of the risk strata and informs interpretation of results. PRMs estimate the probability of the outcome, based on the observed covariates for each unit record. These probabilities quantify the risk of the outcome, and can be used to stratify unit records into different risk groups that are defined in the post-model estimation phase.

Predicted probabilities are generally expressed as percentages. These percentages refer to the likelihood of the outcome predicted by the model. For example, if a model estimates a hospitalisation risk of 90%, this means that nine out of 10 such people in the study can be expected to be hospitalised.

The positive predictive value (PPV) refers to the proportion of people deemed by the model to be high-risk individuals who are truly high-risk. True positives for these analyses are people who were hospitalised in the prediction period. Using the full model from Study 5, the relationship between threshold values, PPV and sensitivity is shown in Figure 6. As the risk score threshold increases, the PPV generally increases and sensitivity decreases.

Threshold choice – the point at which patients are deemed to be at high risk – involves balancing model accuracy, patient volume, and appropriateness of patients identified. It is common practice in performance reporting to use quintiles, deciles or other percentiles to stratify results. Percentile thresholds can be used to create strata of equal size, and to help ensure adequate sample size to compare performance across risk groups.

Figure 6 Comparison of different risk thresholds to define high-risk group membership (Study 5)

	Number in high risk group	Risk score range for high risk group (%)	Number of true positives in high risk group (acute emergency admissions in prediction year)	Positive predictive value (% true positives in high risk group)	Sensitivity (% true positives among all true positives in high risk group)
Percentile Threshold					
Top quintile	52,666	>12.7	13,132	24.9	54.8%
Top decile	26,333	>20.1	8,834	33.5	36.9%
Top 5%	13,167	>29.1	5,503	41.8	23.0%
Probability Threshold					
Predicted probability > 50%	3,251	>50	1,847	56.8	7.7%
Predicted probability > 60%	1,581	>60	995	62.9	4.2%
Predicted probability > 70%	629	>70	442	70.3	1.8%
Predicted probability > 80%	187	>80	139	74.3	0.6%
Predicted probability > 90%	21	>90	15	71.4	0.1%

Note: The total population for Study 5 was 263,328 people. Of these, 23,966 had an acute emergency admission during the 12-month prediction period.

Study 5, the most inclusive of the five studies, represents the general population (263,328 people) where most individuals had a low probability of hospitalisation in the following year (23,966; 9.1%). As a result, few people had high risk scores. For example, only 187 individuals had risk scores above 80%. Small high-risk groups may be desirable for certain clinical applications, such as when the intervention is expensive or clinical capacity constraints exist (Figure 6).

In addition to considering high-risk group size and predictive performance, it is also important to be cognisant of the characteristics of patients designated to be high-risk. More stringent threshold definitions with higher probability cut-offs increase the proportion of the very ill in the high-risk group. Figures 7a to 7c show the effect of varying the threshold for risk on the composition of the high-risk group.

For example, in Study 5, 1.1% of people died during the prediction period (Figure 7a). If the high-risk group was defined as the top quintile (20%) of patients at highest risk, then it would have included just over 4% of people at the end-of-life (Figure 7b). However, if the high-risk group was defined as the 5% of patients at highest risk, then the group would include a larger proportion of people who are at the end of life (9.9%) (Figure 7c).

As the high-risk threshold definition gets more stringent by capturing a smaller portion of the predicted probability distribution, the high-risk group becomes more concentrated with people with complex health needs.

Varying risk thresholds is one way to tailor analyses so that appropriate individuals are being identified for the intended purpose.

Figure 7a **Composition of Study 5**

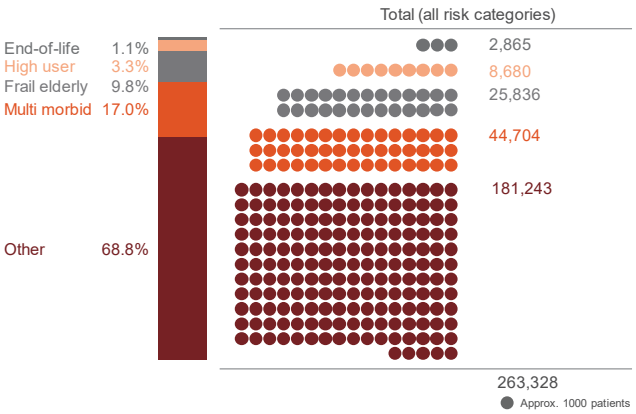


Figure 7b **Composition of 20% of patients in Study 5 at highest risk of admission**

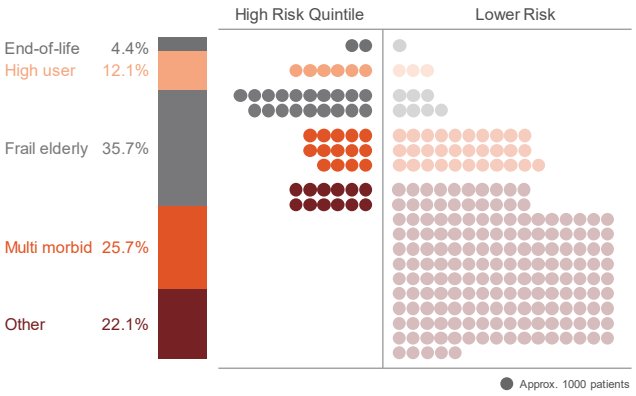
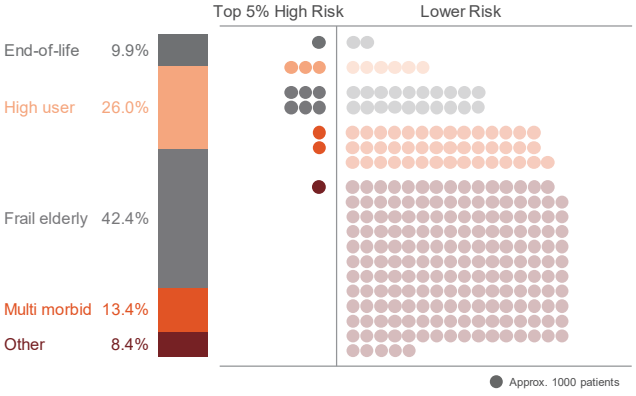


Figure 7c **Composition of 5% of patients in Study 5 at highest risk of admission**



Modelling: Risk factors and data linkage

Changing the selection criteria for study entry and removing variables from the full PRM impacts who is predicted to be in the high-risk quintile. The characteristics of patients predicted to be at highest risk of hospitalisation vary when: (1) variables are excluded from the model, or (2) selection criteria for the study change (Figure 8).

The total number of respondents in Study 5 included nearly all survey participants from the 45 and Up Study. Scenario A in Figure 8 presents the characteristics of the high-risk quintile in Study 5 (52,666 people). The model included variables from all the linked datasets used for this study.

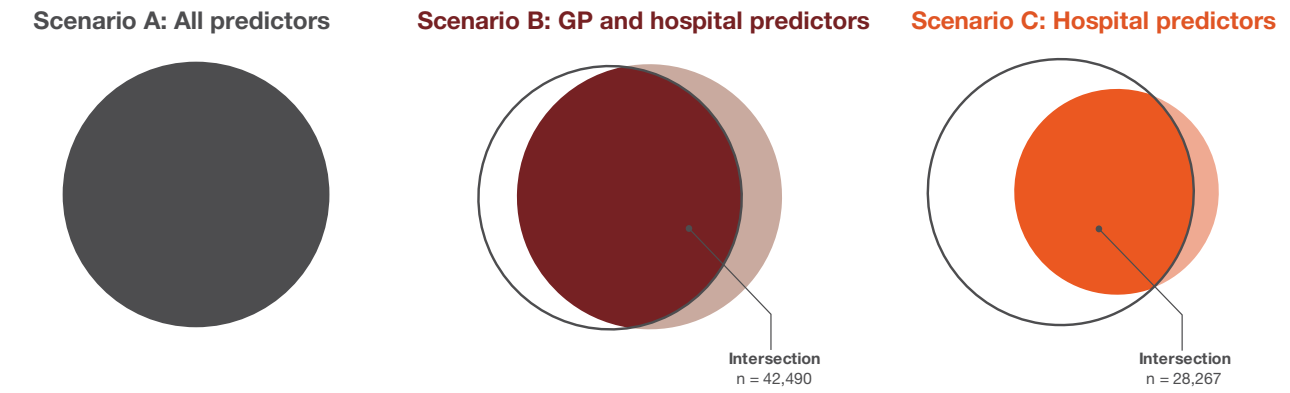
Scenario B shows the composition of the high-risk quintile in Study 5 when all variables from the survey were excluded from the model (socio-demographic and self-reported health data).

Scenario C is based on Study 4 and is made up of individuals who were discharged from hospital or visited the ED in the last three years (30,990 people).

Of the high-risk people in Scenario A, 80.7% were also identified in Scenario B. The high-risk group in Scenario B contains more people with comorbidities (59.0%; up 3.1 percentage points).

A comparison between Scenario A and Scenario C shows how selection decisions impact the composition of the high-risk group. The inclusion criteria identified sicker individuals from the 45 and Up Study. In comparison to the high-risk quintile in Scenario A, the high-risk quintile in Scenario C had a greater percentage of respondents with comorbidities (63.0%; up 7.1 percentage points).

Figure 8 Effect of combining datasets on predictive power and quintile composition



Scenario A: High risk characteristics	
% Frail elderly	42.3%
% High users (past)	13.4%
% Multimorbid	55.9%
% Fair/poor health	39.5%
% Very old (85+ years)	18.7%
% End-of-life	4.4%

Scenario B: High risk characteristics	
% Frail elderly	38.2%
% High users (past)	8.9%
% Multimorbid	59.0%
% Fair/poor health	41.5%
% Very old (85+ years)	19.1%
% End-of-life	4.0%

Scenario C: High risk characteristics	
% Frail elderly	40.4%
% High users (past)	20.4%
% Multimorbid	63.0%
% Fair/poor health	32.0%
% Very old (85+ years)	25.6%
% End-of-life	5.8%

Note: The sub-populations in Figure 8 are not mutually exclusive and therefore the percentages in each scenario sum to over 100%.

Risk persistence

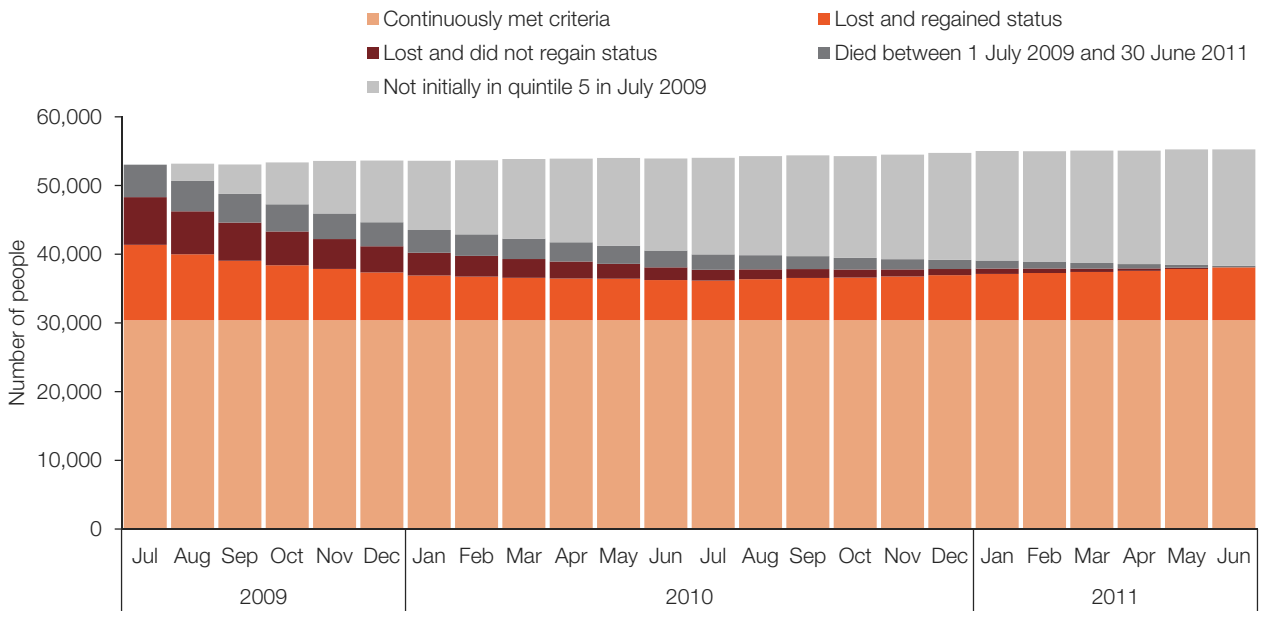
Risk status, especially high-risk status, can be handled as either varying or fixed over time. Patients may move in and out of risk categories over time regardless of whether an intervention is undertaken (Figure 9). The persistence of hospitalisation risk should be taken into account, both for developing intervention strategies and for interpreting results.

The change in predicted risk status over time is a reflection of the risk predictors included in the model. For example, age and history of hospitalisation vary over time while ethnicity does not. A bias is introduced if risk status is conceptualised as time-fixed when it is driven by time-varying factors.

Figure 9 shows the changes in risk composition for the patients falling into the high-risk quintile in Study 5 (Scenario A). For each person in the cohort, the risk was calculated at the start of each month, using the parameters from the PRM. More than half of the people in the high-risk quintile continuously met the high-risk criteria in the following two years. A second group of people were initially in the high-risk quintile, but moved in and out of the high-risk group in subsequent months. A third group of people initially in the high-risk quintile subsequently became lower risk and remained low risk. A fourth group comprised people initially in the high-risk quintile but who died during a subsequent month. The final group of people were not initially high risk but became part of the high-risk quintile subsequently.

Those that moved into a lower-risk group over time may be an example of the regression to the mean process where risk diminishes regardless of whether an intervention was undertaken. The proportion of people who became lower risk is partly determined by the variables used in the model and whether they are fixed over time. In this model, variables such as current age and previous hospitalisations are time-varying.

Figure 9 Changes in risk quintile composition over a 24-month period



Section 2:

Applying PRM to performance assessment for 30-day readmissions to hospital

Recent studies have explored the usefulness of developing PRMs for the purposes of assessing institutional or provider performance, particularly since a proportion of disease-specific events, such as readmissions, are thought to be preventable.[23,24]

As is the case when using PRMs for case-finding patients at risk of a health event, a few key questions apply to using PRMs for performance measurement:

- Who is at risk of the event?
- What is the event?

Additional considerations for performance measurements include:

- To which organisation is performance attributed?
- Are performance comparisons fair?

Who is at risk of the event, and their level of risk, is relative to the underlying population that is used to build the PRM. Decisions about study group inclusion affect the calculation of an event's probability. The distribution of the risk of an event that is estimated by PRMs depends in large part on the selected population of interest.

For instance, age is an established predictor of health. On average, the risk of a poor health outcome is higher for older versus younger people. Using the risk of poor health in a younger population as a reference group, the probability distribution of poor health in older people is expected to shift upwards, reflecting the fact that risk increases with age.

Deciding on the target population is the first step in contextualising predictions. The second is to be clear about whether the source population used for the PRM to estimate risk is representative of the population that stakeholders want to make inferences about. Who is included in the calculation of risk will dictate the generalisability of the estimated predictions to the population of interest.

PRMs developed for performance measurement seek to estimate the probability of events that are amenable to preventive action. The source population from which events are identified will influence how many events are counted. Many healthcare systems report unplanned readmissions to hospital as an indicator of performance to reflect the quality of care received in hospital and follow-up and community-based services after hospital discharge. Although some readmissions may be unavoidable, this is a useful indicator for identifying areas for patient care improvement and efficient resource use.

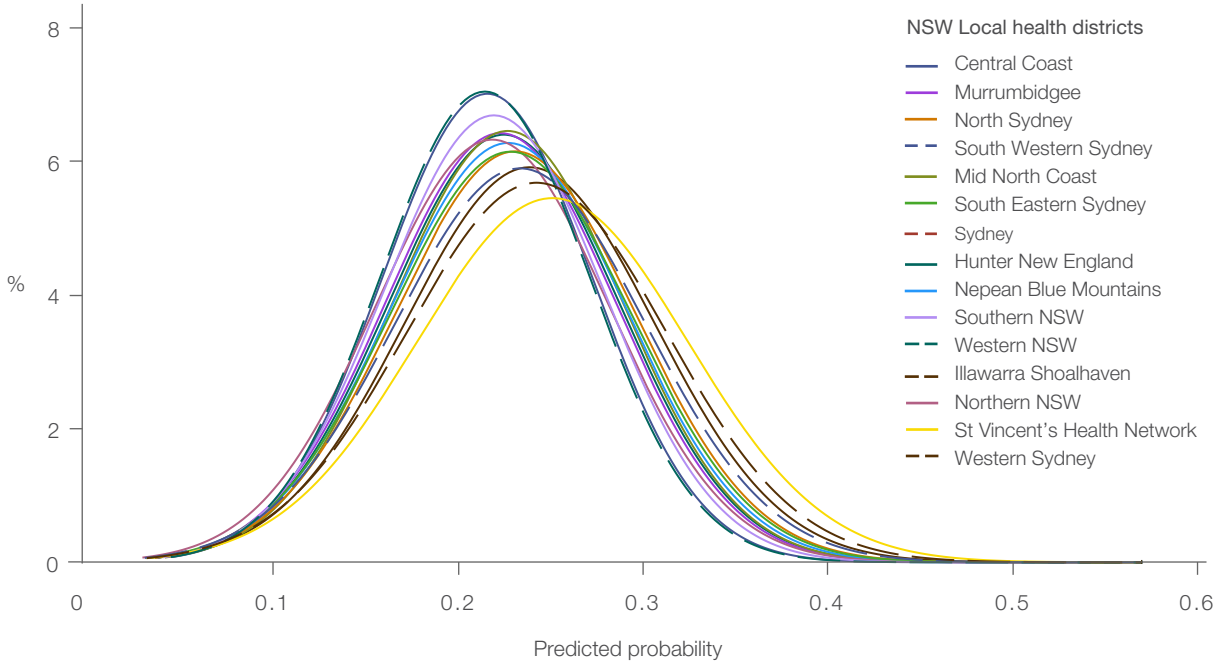
Hospital readmissions: Local health district performance

The decision to attribute performance to a specific level of the healthcare system depends on who was included in the study population and whether the performance predictors in the model are comprehensive enough to support fair comparisons.

Providing healthcare is a complex task involving multiple care providers from different disciplines, specialties, organisational contexts and geographical locations. Careful interpretation of the estimates of a PRM is necessary to avoid overstating the meaning of the estimates.

To inform attribution, the predicted probability of the event can be stratified into categories of risk. This highlights whether overall performance is driven by one or more groups of patients. Risk stratification can also guide decisions about patient care pathways. For example, high-risk patients may be referred to more intensive care pathways instead of remaining under observation. PRMs can be used to identify where risk concentrates to help resource allocation decisions and contextualise geographic differences in performance. As such, stratification can provide more insight to the continuum of care received by different types of patients.

Figure 10 Distribution of predicted risk of CHF readmission by LHD, 2012 to 2014



Distribution of risk

The distribution of the risk of an event varies according to the characteristics of study populations. A model that predicts the probability of an event bases its calculation of risk on the combination of measured factors that are believed to be associated with the outcome. When applied to separate populations it may yield overlapping, and in some cases different, probability distributions.

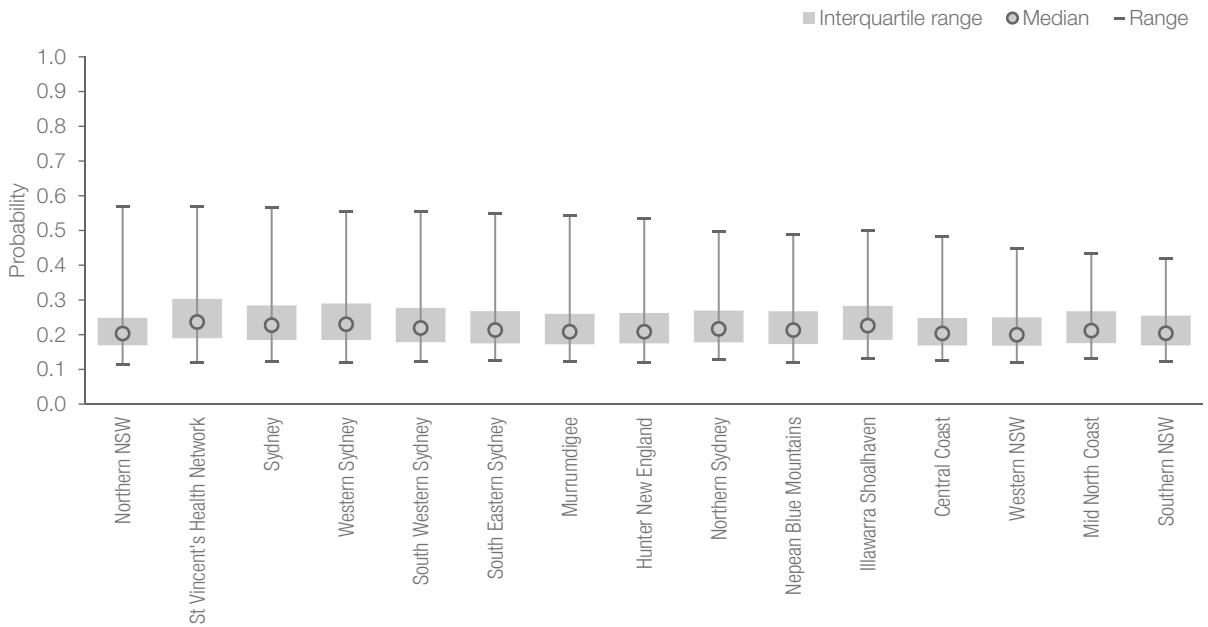
Congestive (chronic) heart failure (CHF) is a chronic condition that causes the heart to ineffectively pump blood and weaken over time. Each local health district's (LHD) probability distribution for the risk of readmission among patients with an index admission for CHF is shown in Figure 10. The smoothed distributions for the risk of a readmission vary in width and height (narrow versus wide indicating the range of risk).

The different risk profiles across LHDs is depicted by the smoothed distribution curves with those appearing further to the right having a greater concentration of higher-risk patients (Figure 10).

Most LHDs showed a wide range of readmission risk with high-risk outliers that reached probabilities of 0.5 to 0.6. However, some rural LHDs had a narrower range. This may be explained in some LHDs by patients seeking services outside of NSW. For example, patients in Southern NSW tend to seek care in the Australian Capital Territory (ACT). The urban St Vincent's Health Network had the highest median (0.24) followed by Western Sydney (0.23).

Looking across each LHD's patient population, Northern NSW and St Vincent's Health Network had the greatest range in predicted probabilities of readmission (each ranging from 0.11 to 0.57) (Figure 11).

Figure 11 Predicted probability range by LHD, 2012 to 2014



Stratifying risk

Stratified analyses of the predicted risk of readmission can help organisations understand how overall performance is affected by different risk groups. They can also be used for assessing performance associated with interventions that target high-risk populations. They can assist clinicians in understanding what is driving overall readmission rates and reflect on intervention strategies.

Extending work previously completed by BHI[3,20], a prediction model was developed and validated for the purposes of risk-adjusting hospital performance, specifically for 30-day readmissions among patients with CHF. The study captured admissions to public hospitals for CHF among patients aged 15+ years in NSW.

Using the same cohort and prediction model that adjusted for patient case-mix differences, the predicted probability of a 30-day readmission to hospital was used to stratify patients into risk quintiles. The objective of this work was to compare, within the risk strata, each LHD's observed and expected performance with regard to 30-day readmissions to hospital.

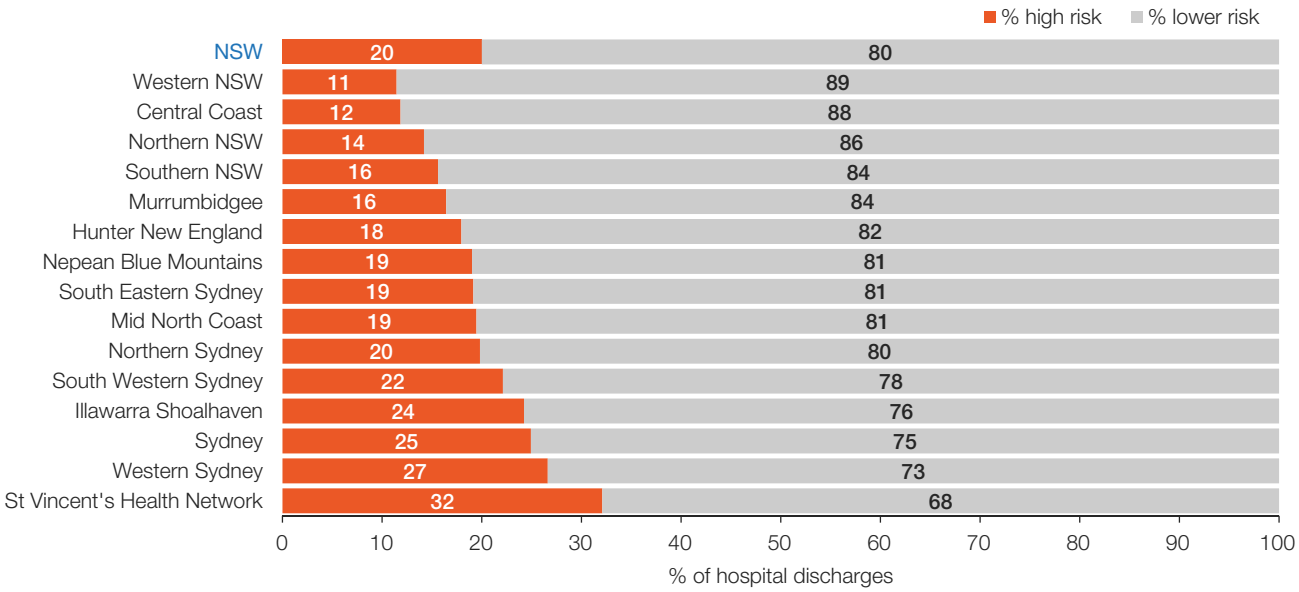
Methodology

The probability of a 30-day readmission for each hospital discharge was estimated from a competing risks regression model that adjusts for age, sex, Elixhauser comorbidities and the number of acute admissions for CHF in the previous year (full model and cohort description are described elsewhere).[22] A flow chart outlining the cohort exclusions, predictors, subhazard ratios, p-values and confidence intervals for the final model are shown in Appendix 2.

Once the model was estimated, the predicted probability of readmission for each discharge was classified into quintiles and labelled from 1 (lowest risk) to 5 (highest risk).

Knowing where risk concentrates geographically can inform resource allocation decisions. In each LHD, patients were categorised into risk quintiles and the observed and expected rates of readmission were calculated. LHD quintiles with fewer than 50 discharges in the three-year study period are not shown.

Figure 12 Percentage of high- versus lower-risk CHF readmissions by LHD, July 2012–June 2015



The expected readmission rate was calculated by summing the predicted probabilities, for each LHD, in the five risk quintiles and then dividing the sum by the total number of discharges in that same quintile. The observed rate of readmission was calculated by summing the total number of readmissions in each LHD risk quintile and then dividing it by the total number of discharges in that same quintile.

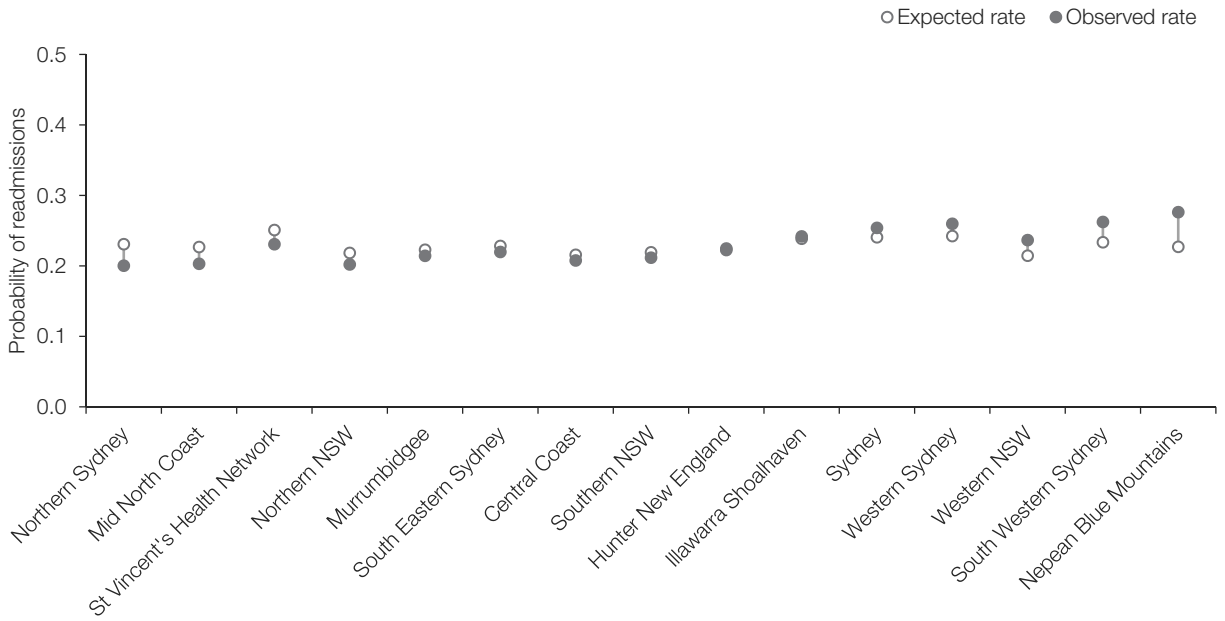
Variation at the LHD level

The predicted probabilities of readmission across NSW were sorted and then divided into quintiles. Statewide, the high-risk quintile captured patients whose predicted probability ranged from 0.29 to 0.57. Within LHDs, the higher risk group was defined as patients with a predicted probability of 0.29 or more.

Almost a third (32%) of CHF patients who were discharged from St Vincent's Health Network had a high probability of readmission whereas in Western NSW and Central Coast LHDs 11% and 12%, respectively, of patients did so. This means that patients considered to be at higher risk of a readmission are not evenly distributed across NSW (Figure 12).

The non-stratified observed and expected rates for each LHD give an overall view of performance (Figure 13). Whereas St Vincent's Health Network had a greater percentage of discharges with a high probability of readmission (32%) compared to other LHDs, its observed rate of readmission was lower than expected according to the PRM (0.23 versus 0.25, respectively). The discharges with a higher probability of readmission in Nepean Blue Mountains represented 19% of total discharges yet the observed rate of readmission exceeded those expected by the PRM (0.23 versus 0.28).

Figure 13 Observed and expected rate of CHF readmission at the LHD level, July 2012–June 2015

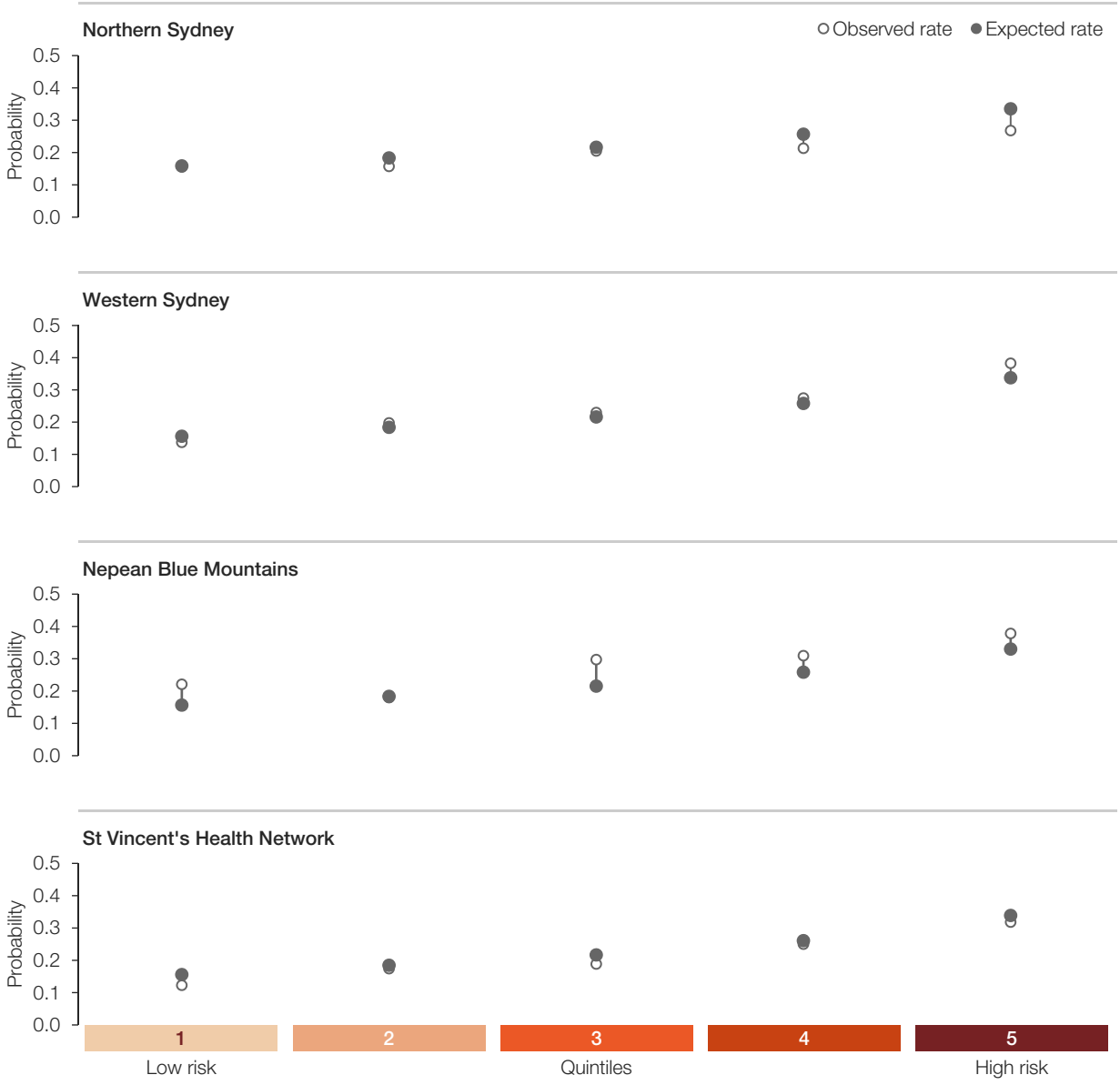


Variation in performance within risk strata

Regional variation in performance within each LHD's low- to high-risk groups shows differences in performance. In selected LHDs, the observed and expected rates were similar. One exception was the high-risk quintile for Northern Sydney where the observed rate was below the expected rate. In most risk quintiles for Nepean Blue Mountains, the observed rate was above the expected rate (Figure 14).

The results from these analyses provide a sense of how patients fare on a low- to high- risk scale in terms of a readmission event. They inform whether this variation is important at a regional level and facilitate discussions on resources and management across levels of the healthcare system, particularly with primary care providers who can play a role in preventing readmissions. A patient's risk at the time of discharge informs decisions about the intensity of follow-up care required.

Figure 14 LHD observed and expected rates, and NSW observed rates of 30-day CHF readmission, 2012-2014



Limitations

The assumption in these analyses is that the differences in the observed and expected number of readmissions are due to real differences in the quality of care as opposed to the effect of other factors or the model fit. We do not publicly report on small providers and each LHD's quintile had to have at least 50 index admissions to be included in the graphs. For this reason, Far West LHD was not shown.

The applicability of a PRM ultimately lies with whether results resonate with clinicians. Collaboration between researchers, healthcare managers, clinical teams and patients is important for validating a PRM. While PRMs can be tools for guiding clinical decisions, physicians have access to patient feedback and perspectives that enhance the relevance of statistical models.[25]

Appendices

Appendix 1: Cohort definitions

The implications of changing the inclusion and exclusion criteria were explored by defining five separate study populations. Studies 1–5 differed by their inclusion criteria and data sources (Figure A1).

The characteristics of patients that were predicted to be at highest risk of hospitalisation changed depending on the variables included in the statistical models. The variables used in Scenarios A–C are shown in Figure A2.

Figure A1 Description of study populations

	Study 1	Study 2	Study 3	Study 4	Study 5
Inclusion criteria	Discharged from hospital in 2008–2009	Discharged from hospital in 2008–2009	Discharged from hospital in 2006–2009	Discharged from hospital or used ED in 2006–2009	Discharged from hospital or used ED, primary care or pharmacy in 2006–2009
Hospitalisation in 2008–2009	69,388	69,395	63,395	69,395	69,395
Hospitalisation in 2006–2007	n/a	n/a	65,043	65,043	65,043
ED attendance in 2006–2009	n/a	n/a	n/a	20,286	20,286
MBS or PBS records in 2006–2009	n/a	n/a	n/a	n/a	108,604
Total	**69,388**	**69,395**	**134,438**	**154,724**	**263,358**

Figure A2 Predictor variables included in Scenarios A–C

	SCENARIO A Hospital + GP + Survey indicators	SCENARIO B Hospital + GP indicators	SCENARIO C Hospital indicators
Study cohort	Study 5	Study 5	Study 4
Age at end of study selection	✓	✓	✓
Gender	✓	✓	✓
Income	✓	✓	✓
IRSD	✓	✓	✓
Remoteness	✓	✓	✓
Indigenous	✓	✓	✓
Currently married	✓	✓	✓
Self-reported comorbidities	✓	✓	✓
English spoken at home	✓	✓	
Number of medications	✓	✓	
Self-reported mental health	✓	✓	
Self-reported BMI	✓	✓	
Smoking status	✓	✓	
Drinking alcohol status	✓	✓	
Self-reported health status	✓	✓	
Number of GP visits in previous 12 months	✓	✓	
Number of acute admissions in previous 12 months	✓		✓
Number of ED visits in previous 6 months	✓		✓
Admitted via ED for last admission in previous 12 months	✓		✓
Length of stay for last admission in previous 12 months	✓		✓
Have people to depend on	✓		
Mobility limitation	✓		
Recent falls	✓		

Appendix 2: Methods for CHF readmissions

The cohort of CHF patients was the same as that used in a previous report from BHI.[20] Following exclusions, the final index cohort contained 33,450 periods of care (Figure A3).

The predictors included in the model, the subhazard ratios, the p-values and the confidence intervals for the final model are shown in Figure A4. These are the same as those in the previous report from BHI.[20]

Figure A3 Cohort inclusion criteria for patients admitted to hospitals for CHF

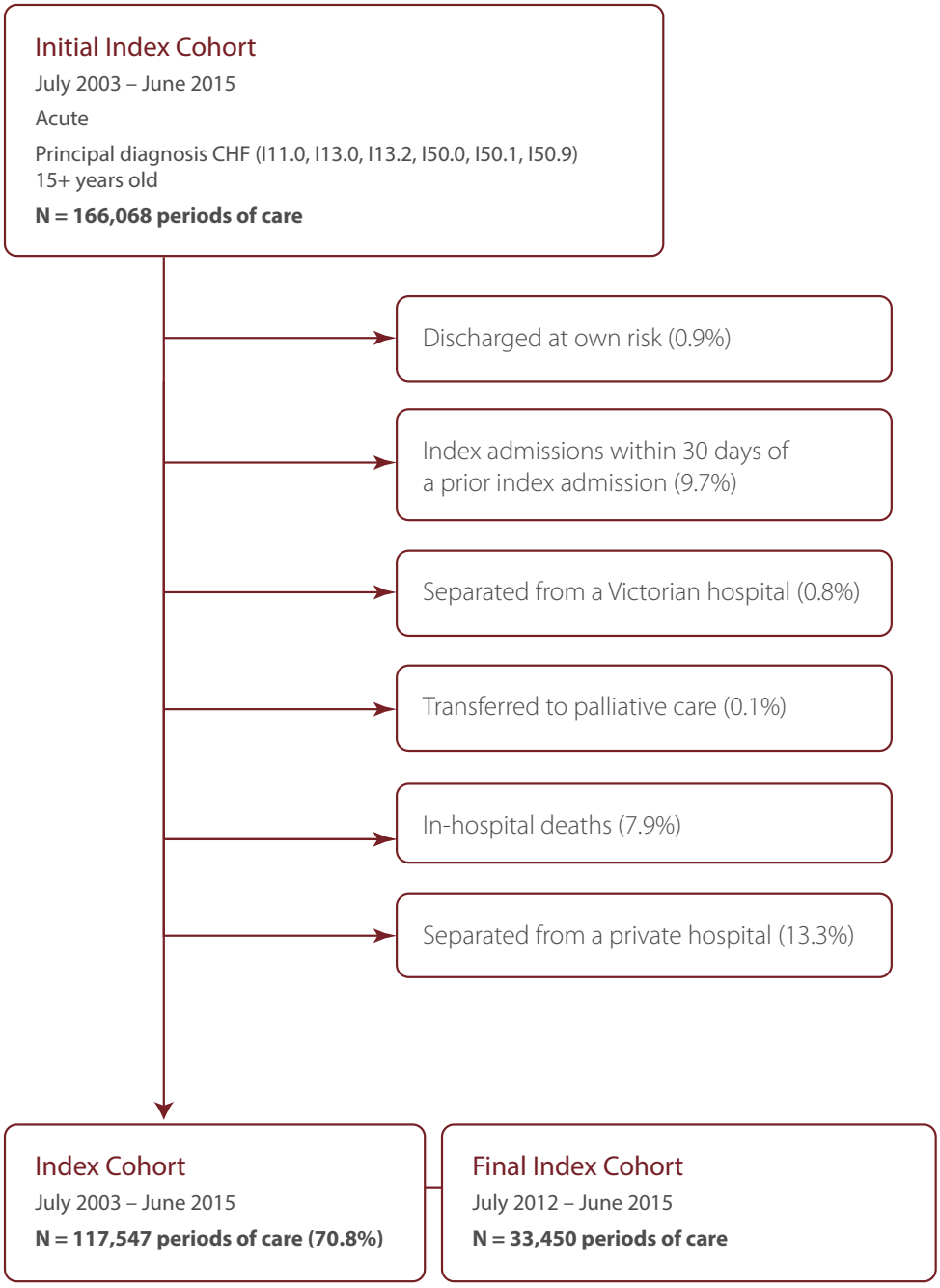


Figure A4 Predictors included in the model for predicting the risk of readmission within 30 days of discharge among patients with CHF

Predictors	Subhazard ratio	P-value	(95% Conf. Interval)
Age (per 1 year increase)	1.00	<0.001	(1.00-1.01)
Female	0.93	0.001	(0.89-0.97)
History of CHF	1.33	<0.001	(1.26-1.41)
Cardiac arrhythmia	1.05	0.023	(1.01-1.10)
Other neurological disorders	1.17	0.012	(1.04-1.33)
Chronic pulmonary disease	1.21	<0.001	(1.16-1.27)
Diabetes (complicated)	1.10	0.001	(1.04-1.16)
Hypothyroidism	1.20	0.001	(1.08-1.34)
Renal failure	1.21	<0.001	(1.15-1.28)
Liver disease	1.12	0.025	(1.01-1.24)
Peptic ulcer disease, excluding bleeding	1.33	0.02	(1.05-1.69)
Metastatic cancer	1.28	0.003	(1.09-1.51)
Rheumatoid arthritis/collagen	1.27	0.007	(1.07-1.52)
Coagulopathy	1.17	<0.001	(1.11-1.23)
Fluid and electrolyte disorders	1.15	<0.001	(1.10-1.20)
Deficiency anaemia	1.13	<0.001	(1.06-1.20)
Alcohol abuse/drug abuse/psychoses	1.21	0.002	(1.07-1.36)
Dementia	1.13	0.010	(1.03-1.23)

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Acknowledgements

The Bureau of Health Information (BHI) is the main source of information for the people of NSW about the performance of their public healthcare system. A NSW board-governed organisation, BHI is led by Chairperson Professor Carol Pollock and Chief Executive Dr Diane Watson.

The analysis was led by Dr Tracy L. Johnson and undertaken with the support of Australian-American Health Policy Fellowship 2016–2017 which is supported under the Centre for Health Economics Research and Evaluation, University of Technology Sydney, by a grant from the Commonwealth of Australia as represented by the Department of Health (DOH). DOH had no role in study design; in the collection, analysis, and interpretation of data; in the writing of the report.

The fellowship was hosted by BHI, which provided mentorship and statistical support. The information and opinions contained in it do not necessarily reflect the views or policy of the Centre for Health Economics Research and Evaluation or the Commonwealth of Australia (or the DOH).

BHI would like to thank:

- The Sax Institute for access to the 45 and Up Study and for linkage to the Medicare Benefits Scheme and the Pharmaceutical Benefits Scheme
- NSW Ministry of Health for access to the Emergency Department Data Collection, the Admitted Patient Data Collection and the NSW Register of Births Deaths and Marriages for access to death data, and the Centre for Health Record Linkage for facilitating the record linkage
- Dr Peter Lewis, Director of the Central Coast Public Health Unit, for sharing his expertise.

BHI's team of analytics, research, corporate, design and communications professionals expertise made this report possible.

bureau of health information

About the Bureau of Health Information

The Bureau of Health Information (BHI) is a board-governed organisation that provides independent information about the performance of the NSW public healthcare system.

BHI was established in 2009 to provide system-wide support through transparent reporting.

BHI supports the accountability of the healthcare system by providing regular and detailed information to the community, government and healthcare professionals. This in turn supports quality improvement by highlighting how well the healthcare system is functioning and where there are opportunities to improve.

BHI manages the NSW Patient Survey Program, gathering information from patients about their experiences in public hospitals and other healthcare facilities.

BHI publishes a range of reports and tools that provide relevant, accurate and impartial information about how the health system is measuring up in terms of:

- Accessibility – healthcare when and where needed
- Appropriateness – the right healthcare, the right way
- Effectiveness – making a difference for patients
- Efficiency – value for money
- Equity – health for all, healthcare that's fair
- Sustainability – caring for the future.

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