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Figure 3 -Persistence Data.xls

Predictive Risk Modelling under Different Data Access Scenarios: Who is Identified as High-Risk and for How Long?

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ABSTRACT

Objective

This observational study critically explored the performance of different predictive risk models simulating three data access scenarios, comparing: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status over time.

Methods

Cross-sectional health survey data (2006-09) for more than 260,000 Australian adults 45+ years were linked to longitudinal individual hospital, primary care, pharmacy and mortality data. Three risk models predicting acute emergency hospitalisations were explored, simulating conditions where data is accessed through primary care practice management systems, or through hospital based electronic records, or through a hypothetical 'full' model utilizing a wider array of linked data. High-risk patients were identified using different risk-score thresholds. Models were reapplied monthly for 24 months to assess persistence in high-risk categorization.

Results

The three models displayed similar statistical performance. Three-quarters of patients in the high-risk quintile from the 'full' model were also identified using the primary care or

hospital based models, with the remaining patients differing according to age, frailty, multi-morbidity, self-rated health, polypharmacy, prior hospitalizations, and imminent mortality. The use of higher risk prediction thresholds resulted in lower levels of agreement in high-risk designation across models and greater morbidity and mortality in identified patient populations. Persistence of high-risk status varied across approaches according to updated information on utilization history, with up to 25% of patients reassessed as lower-risk within one year.

Conclusion/Implications

Small differences in risk predictors or risk thresholds resulted in comparatively large differences in who was classified as high-risk and for how long. Pragmatic PRM design decisions based on data availability or projected high-risk patient numbers may therefore influence individuals identified as high-risk, overall case-mix, and risk persistence. Routine data linkage would enable greater flexibility in developing and optimizing predictive risk models appropriate to both case-finding and performance measurement applications.

Strengths and Limitations

- This simulation demonstrates how a detailed population analysis may be used alongside statistical testing results to ensure that algorithms are fit to purpose.
- Linked population and use data maximize flexibility in developing PRM specifications appropriate to case-finding and performance measurement applications.
- Oversampling of elderly and rural residents and a low survey response rate (18%) limit the generalizability of these model-specific descriptions of case-mix, consistency in high-risk designations, and risk persistence.[1]
- In practice, high-risk group agreement across different PRM applications could be less than estimated, due to differences in risk factor measurement, base populations, prediction periods, and other modeling assumptions held constant here.

INTRODUCTION

To address population health objectives and expenditure growth associated with aging populations and increased chronic disease prevalence, governments and health systems in the UK, Australia, the US and elsewhere are exploring the use of predictive risk modeling (PRM) to better target and integrate services.[2,3,4,5,6] PRM algorithms calculate the probability that a specific patient will experience a future event, such as hospitalization, based on their unique risk profile. Two different but related applications include identifying individual patients for intervention ("case-finding") and creating high-risk population segments for focused healthcare performance analysis.

Internationally, considerable variability exists in PRM implementations due to differences in health system organization and financing, which affects perceptions of accountability and data access. The entity responsible to administer PRM can be hotly debated, as exemplified by the UK's shift from a centrally-administered algorithm to practice-specific adaptations.[7] PRM requires access to detailed, patient-level risk factor and health service information, ideally, across clinical and community settings and over time. However, for many countries data are non- or partially-linked. Although important to intervention design, limited comparative information exists regarding high-risk patient characteristics identified in different data environments.[8]

A number of review studies compare alternative PRMs with focus on predictive statistics rather than resultant patient profiles and risk persistence.[9,10,11,12,13] Validation studies of

specific instruments also focus on statistical performance, with some also estimating future per-person spending of identified high-risk patients.[14,15,16,17] Billings et al. (2013) is one of the few studies to quantify gains in prediction performance of a hospital-oriented PRM through sequential addition of emergency, outpatient, and general practice information. They also observe that PRMs using non-hospital data identified more lower-acuity patients which could present earlier intervention opportunities.[18] Two studies have found that high-risk population subgroups differ according to the persistence of high-risk status over time.[19,20]

Australia's planned use of PRM in state and national trials provides an opportunity to examine patient profiles under different data access scenarios. For example, the Commonwealth's health care homes initiative will employ an automated PRM to identify primary care patients who are at-risk of hospitalization and assess them for allied health service needs and develop multidisciplinary care plans.[21] In parallel, NSW Health will implement an integrated care initiative that will use a hospital-oriented algorithm to identify recently discharged patients who need similar supports.[22] Both programs will require that GPs use a standardized care clinical screening tool to determine eligibility for specific services. Despite patient identification efforts that rely on different data sources and PRM tools, both programs focus on enhanced outpatient care provision to high-risk patients. The likelihood of patient overlap in separately-administered high-risk patient identification efforts is unknown.

This research critically explored the comparative patient identification performance of different PRM algorithms, simulating three common data access scenarios: a 'full' model using all available information, a primary care data only ("GP") model, and a hospital data only ("hospital") model. Using models that draw elements from planned Australian PRMs, we assessed: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status.

METHODS

Data Sources

The PRMs used population survey and linked health administrative data for participants in the 45 and Up Study. The Sax Institute's 45 and Up Study is drawn from the population of the state of New South Wales (NSW), Australia. Prospective participants were randomly sampled from the Department of Human Services (formerly Medicare Australia) enrolment database, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. A total of 266,942 participants 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. With approximately 18% of those invited responding, participants represent about 11% of the NSW population aged 45 years and older.[23]

This analysis also incorporated information about respondents' health service use and mortality, obtained with patient consent from administrative health databases and linked to their survey responses. This included public and private sector hospital separation and ED presentation information from the NSW admitted patient and emergency department data collections (APDC and EDDC). It also included information about subsidized general practice (GP) care from the Medicare Benefits Schedule (MBS) and prescription drug use form the Pharmaceuticals Benefits Scheme (PBS). Fact of death information was obtained from the NSW Registry of Birth Deaths and Marriages (RBDM).

The Sax Institute used a unique identifier provided from the Australian Department of Human Services to link survey responses to the MBS and PBS that the Department of Human Services (DHS) provided. Using probabilistic methods, the Centre for Health Record Linkage conducted the data linkage of APDC, EDDC and RBDM datasets.

Cohort definition

We created a NSW cross-sectional, population-based cohort (n=263,328) that includes both primary care users as well as those with recent hospitalizations, as these are common target populations in medical home and integrated care initiatives, including those in Australia.

Prediction Outcome and Prediction Period

The PRM algorithms estimated each respondents' probability of experiencing one or more acute emergency admissions during Fiscal Year 09/10. High-risk patients were

identified as those in the highest quintile (top 20%) of predicted probabilities of hospitalization. Alternative high-risk thresholds – i.e., the top 5% or 10% -- were also examined.

Predictor and descriptive variable definitions

A consolidated list of predictor variables was drawn from tools in use in the Australian integrated care and health care homes trials, which included validated Canadian and UK case-finding PRMs and an Australian-developed primary care assessment tool.[24,25,26,27] (See Appendix A.) Where data limitations prevented matching measure specifications from the three tools, variable definitions drew from previous work associating the predictor with hospitalization.[28,29,30,31] Covariates included self-reported measures from the 45 and Up Study (including socio-demographics, social support, health status, health behaviors, and functional status) as well as utilization history from the APDC, EDDC and MBS datasets. (See Table 1.) Missing survey responses were included as discrete values under the assumption that programs would likely attempt to estimate risk for patients with missing information, rather than exclude them from consideration for services. Predictor variables were used as PRM covariates and as descriptive variables to characterize the resultant high-risk populations. Additional analysis variables identifying clinical subgroups were created by collapsing or combining PRM predictors.

Table 1: Variables used in predictive risk models

	Model 1 'Full' model	Model 2 Primary care setting	Model 3 Hospital setting	Sensitivity Analysis: Model 2 with GP use
Sociodemographics/Social support				
Age, gender, Aboriginal status, geographic remoteness, SES, marital status	X	X	X	X
Language spoken at home	X	X	-	X
Income, social isolation	X	-	-	
Health status and health behaviours				
Health condition count	X	X	X	X
Self-rated health, polypharmacy, anxiety/depression, BMI, smoking status, unsafe alcohol use	X	X	-	X
Functional status, falls	X	-	-	
Prior health service utilisation				
Previous hospitalisations, admission via ED, length of stay of previous hospitalisation, previous ED use	X	-	X	-
Primary care accessibility				
GP use	X	-	-	X
Total number of variables	**23**	**14**	**11**	**15**

Socio-Demographics and Social Support Predictors

Socio-demographic and social support variables (age, gender, indigenous status, marital status, language, geographic remoteness, socioeconomic status, income, and social isolation) were obtained from the baseline questionnaire. Using birth date, baseline age was updated to reflect respondent age during prediction and subsequent measurement periods. Quintiles of socioeconomic status were derived from residential postcode using the Australian Bureau of Statistics (ABS) Index of Relative Socioeconomic Disadvantage (SEIFA IRSD).[32] Similarly, the ABS Accessibility Remoteness Index of Australia Plus (ARIA+) was used to classify remoteness into major city, inner regional, outer regional,

remote and very remote categories.[33] Indigenous status (yes/no) included those who self-identified as Aboriginal or Torres Strait Islander, or both. Income was based on *"usual yearly household income before tax, from all sources"* and categorized into $10K increments through $70K. Social isolation was identified as a response of "no one" to a survey question that asked, *"how many people outside your home, but within one hour of travel, do you feel you can depend on or feel very close to?"*

Health Status and Health Behaviours Predictors

To ensure consistency in covariate measurement across the three PRM models, all health status and health behavior measures were calculated from the baseline survey even when also available in administrative data. Several predictors consisted of risk factor counts. The health condition count summed self-reported chronic conditions (0, 1, 2, 3+) according to participants' responses to the questions "*Has a doctor ever told you that you have ...*?" or "*In the last month have you been treated for ...?"* The eight conditions counted were: heart disease, diabetes, high blood pressure, stroke, blood clots, cancer, asthma, or Parkinson's disease. The depression/anxiety measure (yes/no) was also derived from these same questions. The polypharmacy variable totaled the number of medications (0, 1-4, 5+) that respondents had "*taken most of the last 4 weeks*", as selected from a list of common medications. The falls count (0,1,2+) was based on the question, "*during the past 12 months, how many times have you fallen to the floor or the ground?*"

Additional predictors were derived from validated items or short standardised scales included in the 45 and Up baseline questionnaire. Self-rated health (SF-1) was reported as excellent, very good, good, fair or poor. The Body Mass Index (BMI) was

collected in Kg/M^2 and responses were classified as underweight (<18.5), normal weight (18.6-25), overweight (26–30), and obese (>30). The question "*are you a regular smoker now?*" was used to assess baseline smoking status. Alcohol use was estimated from self-reports of *"about how many alcoholic drinks do you have each week?"* with unsafe use defined as more than 14 per week (adjusted for 9% under-reporting).[34] Functional capacity was defined according to the Medical Outcomes Study, Short Form 36 Physical Functioning Scale scores, with no limitation corresponding to a score of (100), minor limitation (95–99), mild (85-94), moderate (60–84) and severe limitation (0–59).[35]

Prior Hospital/ED Utilization and Primary Care Accessibility

APDC, EDDC and MBS administrative datasets were used to calculate prior utilization predictors. Variable specifications for the hospitalization-related covariates were based on the Ontario HARP. Utilization predictors included: acute admission six months prior (0,1,2,3+), length of stay of prior acute admission (0-2, 3-7, 8-14, 15-30, 31+), admission via emergency department (yes/no), emergency department visits six months prior (0,1,2,3,4+). GP visits in the prior twelve months were also calculated and classified as (0, 1-3,4-5, 6-11, 12+).[36] Look-back periods for prior hospital, ED, and GP service use were calculated from the start of the prediction period (July 1, 2009.)

Population Subgroups

Frail elderly were defined as individuals 65+years that reported severe physical limitations and/or 2 or more falls in the last year.[37] Super-utilizers were those with 2+ acute admissions in the previous 6 months. Fair/poor health indicates those whose self-rated health was fair or poor and multi-morbid individuals were those with 2+ health conditions. Those who died during the prediction year are classified as end-of-life. Although these subpopulations were selected because they are often considered clinically distinctive, they are not mutually exclusive designations.

PRM Modeling Scenarios

Three PRM models were developed to simulate high-risk population identification within alternative data environments. PRM-1 ("full model") was built with comprehensive, linked data and used the full, consolidated list of predictor variables to define high-risk status. In addition to data elements routinely available in GP and hospital settings, it included less-commonly collected risk factors such as income, social isolation, and functional status. PRM-2 ("GP model") simulates a primary care-based implementation. Based on the capabilities of the most common practice management software in Australia, GPs were assumed to have electronic access to socio-demographics, language, health/mental health status, and health behaviours. Conversely, the GP model did not include prior hospitalization, ED or GP visit information because common GP practice management software does not track utilization history. While practices often have separate business software that includes GP visits, only very sophisticated practices have the data skills to link business information and clinical information for analysis. We did,

however, conduct sensitivity analyses on our decision to exclude past GP use via a GP+ model that included GP utilisation. Finally, PRM-3 ("hospital model") assumed that primary care patient rosters were matched with hospital administrative data, providing access to patient demographics, health status, as well as past hospital and ED use. This data matching assumption reflected actual practice in Australia's integrated care pilot and ensured consistency in the base population across the three PRM test scenarios. (See Table 1 for model-specific risk predictors).

All models used a logistic regression to predict the outcome of any acute emergency hospitalisation in Fiscal Year 09/10. The extent to which high-risk individuals were admitted to hospital as predicted (positive predictive value) was assessed and the c-statistic was calculated.[38] All statistical analyses were performed in SAS version 9.4 (SAS Institute Inc., Cary, NC, USA).

Descriptive Analysis and Assessment of Persistence

We compared case-mix, identification consistency, and risk persistence among the high-risk populations identified by each model. High-risk persistence refers to the proportion of high-risk individuals that continue to be (or re-achieve) high-risk status. To assess the persistence, we identified individuals in the high-risk quintiles for four models. Two GP models were included in this analysis, with and without GP utilization history as a predictor variable. We recalculated the risk quintile of these high-risk people on a monthly basis over a two-year period, applying updated age and utilization risk factor information. All other risk predictors were measured at solely baseline, so are not time-

varying covariates. Individuals who died during the prediction period were removed from this analysis in the month of their death.

Ethics

The 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC). Additionally, this research, inclusive of data linkage, was approved by the NSW Population and Health Services Research Ethics Committee (HREC/15/CIPHS/42, 04/10/16).

RESULTS

Of the 266,942 participants in the 45 and Up Study, n=266,519 were eligible for inclusion because they used a hospital/ED/medical/pharmacy service between July 2006-June 2009. Of these, n=3182 were excluded as they died prior to the 1-year prediction period (June 30, 2009). An additional n=9 were excluded for possible linkage errors, leaving 263,328 patients for analysis. Characteristics of the full population is provided in Appendix C.

The probability threshold for the high-risk quintiles were low for all models (12.0 - 13.1%). Approximately one-quarter (22.2-24.9%) of patients in the top risk quintile experienced an emergency admission during the prediction year (positive predictive

value) and these high-risk patient admissions represent one-half (48.9-54.8%) of total admissions (sensitivity). Statistical performance of the three PRM scenarios was very similar, with moderately strong c-statistics for all models, ranging .74 to .77.

Despite similarities in predictive accuracy, the three PRM scenarios yielded different high-risk individuals and population characteristics (Figure 1). The 'full model' produced a high-risk population that includes high percentages of frail elderly, multi-morbid individuals and those reporting fair/poor health.

Figure 1: Comparison of High-Risk Quintiles from the Full, GP and Hospital scenarios

Sharing three-quarters (74%) of patients in common with the full model, the primary care model high risk group includes more multi-morbid individuals (62.8% vs. 55.9%) and those in fair/poor health (43.2% vs. 39.5%) but fewer super-utilizers (8.0% vs. 13.4%) and those at the end-of-life (3.9% vs. 4.4%). The hospital high-risk quintile also agreed with the full model one three quarters of the time (77%). Across the three models, the hospital high-risk group includes the lowest proportion of frail elderly (34.4% vs. 42.3%) and those in fair/poor health (27.5% vs. 43.2%) and highest proportion of super-utilizers (14.3% vs. 8.0%). These case mix differences across high-risk quintiles are driven by differences among the one-quarter of patients not shared in common. (See Figure 2.)

Nearly two-thirds (59%) of the top quintile of high-risk individuals were consistently identified within all three models (see Figure 2). As compared to the full model, this

overlap group has higher morbidity and mortality: with multi-morbid individuals (69.6% vs. 55.9%), frail elderly (50.1% vs. 42.3%) in fair/poor health (42.7% vs. 39.5%) and very old (31.4% vs. 18.7%). They are also somewhat more likely to be at the end of life (5.7% vs. 4.4%). As the high-risk threshold is increased to the 90th or 95th decile, positive predictive values increase in the range of 28.3-33.5 and 34.3-41.8 respectively, but the models' intersection decreases, falling to 48% and 39% shared patients, respectively. This results primarily from the GP model diverging from the other two. (Appendix C.)

Figure 2: Intersection of Models for Different High Risk Thresholds

Table 2 summarizes the extent to which characteristics of the high-risk patient cohort changed when using different models or risk prediction thresholds. High-risk group acuity increased dramatically as high-risk thresholds increased. Proportions of very old, frail elderly, multi-morbid individuals, super-utilizers and those who report fair/poor health increased by more than 10 percentage points. With the exception of age and marital status, there was little change (<5 percentage points) in the sociodemographic and behavioral profile of high-risk patients, irrespective of model or high-risk threshold. Although not all population characteristics were explicitly measured in all models (See Figure 1), this did not consistently affect their prevalence in high-risk groups. For example, functional status was measured explicitly only in the full model, but individuals

with severe functional limitations accounted for at least one-third of high-risk quintile patients (32.3-45.5%) across models. In general, patient characteristics with high odds ratios (>1.3) were the most sensitive to modeling specifications. (See Appendix B for odds ratios and Appendix C for selected case-mix characteristics by model and threshold.)

Table 2: Variability in case mix among patients identified as 'high risk' when varying modelling approach or high risk admission thresholds

	Case Mix Changes: Average percentage point spread between minimum and maximum population proportions					
	Same Threshold, Different models "Model Effect"			Same Model, Different Thresholds "Threshold Effect"		
	<5	5-10	>10	<5	5-10	>10
Frail Elderly			X			X
Super-Utilizers (Hospital, ED, GP)			X			X
Individuals reporting Fair/Poor Health			X			X
Very Old (85+ years)		X				X
People taking 5+ Medications			X		X	
Individuals reporting Excellent/Very Good Health			X		X	
Multi-Morbid Individuals		X			X	
Middle-Aged Adults (45-64 years)		X			X	
People at End-of-Life	X			X		
Unmarried Persons	X				X	
Persons with Depression/Anxiety	X			X		
Socio-demographic Groups (Males, Low-Income, Residents of Most Disadvantaged Areas, Rural Residents Non-English Speakers)	X			X		

Figure 3 illustrates that four in five (78.8%) high-risk individuals for the full model and three of four (74.3%) in the hospital model remain persistently high-risk when re-evaluated over a two-year period. For these models, approximately 20-25% of high-risk group members gradually lose high-risk status throughout the first year following identification. High-risk group membership stabilizes thereafter.

Figure 3: Persistence of High-Risk Group Status over Time:
% of Original HR Quintile that are High Risk in Subsequent 24 Months

Reduction in risk status results from individuals no longer meeting the "prior ED" or "prior hospitalization" criteria, which are used to assess risk in the full and hospital models. By contrast, all of the GP high-risk quintile (100%) remained persistently high risk, because only age changed over the two-year period. Unlike the other two models, the GP model did not include prior utilization history, and all other risk factors were measured solely at baseline. While advancing age increases risk status, this analysis focuses on individuals already at highest risk. As a result, for a fixed survey cohort, high-risk status did not vary over time. In the GP+ model that included GP usage history, 12.9% of high-risk individuals identified with the GP+ model lost high-risk status over two years.

DISCUSSION

To effectively leverage PRM as part of the implementation of medical home, integrated care and other quality improvement efforts, stakeholders need to know whether they are

targeting patients at greatest risk of utilisation and to understand how well health systems are currently performing for them. Our study demonstrated sensitivity of case-mix and risk persistence to PRM specifications, and that one cannot rely solely on predictive performance to assess model suitability for either clinical or evaluative purposes.

Among our population-based cohort, all three models resulted in high-risk quintiles that included relatively low cut-points for the risk of admission (12-13%), with one-in-four individuals subsequently hospitalized. The large number of people with lower risk scores meant that the high-risk population was sensitive to varying risk predictors and thresholds. As high-risk thresholds increased, case-mix was increasingly characterized by high proportions of very old, frail elderly, multi-morbid individuals, and those who report fair/poor health. At the 95th percentile, for example, more than one in four high-risk group members had a history of repeat hospitalizations and nearly one in 10 would die during the prediction year. Differences between high-risk groups reflected the strongest PRM predictors, highlighting the need to ensure the modeling specifications are optimized to "find cases" appropriate for the intervention. How long a person remained high-risk depended on the PRM's relative reliance on factors that could change over time – only age and recent utilization history in our models. Risk status was least stable in PRMs that incorporated prior hospital use.

Case Finding Implications

Case-finding PRM applications seek to target interventions by identifying patients at-risk of hospitalization. Our results demonstrate that fully or partially-linked data identified high-risk patients who would not have been classified as such using GP data alone - for example, super-utilizers with multiple prior hospitalisations. In a general practice setting, such patients may not have been targeted for closer monitoring, especially if they were out-of-care or new to the practice. Sharing actionable information across data settings is a clear value-add and often an explicit motivation for predictive risk modeling.

Whether a patient's high-risk status is relatively more persistent or episodic also has bearing on case-finding. For example, if risk manifests episodically, clinical interventions may be short-term and time-sensitive. To identify new at-risk patients in near real-time, the PRM base population may need to be updated and reassessed more frequently. In practice, not all variables commonly used in PRMs are available on a real-time basis, including those (e.g., hospitalization history) that influence risk persistence.[39] If data lags are long, the window of opportunity for intervention may close before providers become aware of a change in risk status.

Performance Measurement Implications

Additional considerations apply for the use of PRM in performance measurement applications. Here, the aim is to define high-risk population segments, for example, to understand how well health systems have been performing for high-risk populations and evaluate the impact of new models of care. PRM-defined population segments could be

used to describe the regional distribution of high-risk populations and to assess past and current service use, morbidity, mortality, and other medical home/integrated care outcomes. Fair and appropriate performance measurement therefore requires a reasonable match between target populations identified via case-finding and corresponding performance measurement populations. Yet in our findings, only three-quarters of patients, at best, were commonly identified using data available in different settings. While the minimum degree of agreement necessary for analysis may differ across performance measurement applications – e.g., program evaluation may differ from on-going health system reporting -- it is clear that clinical intervention and performance populations will not be fully equivalent unless they are using exactly the same data.

Even with identical data, pragmatic data analysis decisions could inadvertently introduce bias. For example, case-finding applications often set risk thresholds high due to clinical capacity constraints,[40] while performance measurement applications may prefer larger risk groups to ensure adequate sample size for analysis. In our simulation, morbidity and mortality dramatically increased as risk thresholds increased. Therefore, creating a larger analysis population by relaxing the PRM high-risk threshold would not only increase sample size (intended), it would also change case-mix (unintended).

Stratified approaches to performance measurement also need to reflect on the persistence of high-risk status relative to the outcome assessment timeframe. Stratified analysis is well-suited for short-term outcomes that are measured soon after patients are classified as high-risk, such as care planning or readmission. However, medical home and integrated

care initiatives often aim to reduce long-term hospitalization rates and costs, measured years later.[41] In our simulation, up to 20% of high-risk patients in the full model and 25% identified via the hospital model would change risk status within a year of identification. From a performance measurement perspective, this means that high-risk patients that become lower risk over time – whether due to usual care or program interventions -- would no longer be counted among the "high-risk" strata for which outcomes are reported, unless methodological steps were employed to retain them.

Theoretically, variation in care could also be reflected in risk status, and persistence of high-risk status could potentially be explored as an outcome of care to be assessed as part of performance measurement. The GP model, with regularly updated risk factor information related to health behaviours and self-rated health, might work well for this purpose. By contrast, the hospital model is highly endogenous, with recent hospitalization history a key determinant in establishing current (hospitalization) risk status. Because risk scores in this instance track with recent hospital use, monitoring hospitalization patterns may provide a more direct means for benchmarking and evaluating variation in care.

Regional differences may emerge in stratified performance outcomes or in high-risk patients' rates of return to lower risk status. Designing meaningful comparisons of performance across sites will require careful consideration. Within the broader high-risk population segment, case mix is likely to differ by clinical site, especially if they implement PRMs tailored to their populations. Even with a standard PRM, known

regional variations in demographics and health status will likely result in some sites having high-risk groups dominated by frail elderly, others by super-utilizers, and still others by the multi-morbid. For certain performance comparisons, it may be necessary to risk-adjust (within risk strata) or further stratify (e.g., by subgroup) to account for this heterogeneity. This area is ripe for additional research.

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Competing Interests

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Evaluation (TLJ), infrastructure support from the Bureau of Health Information (TLJ, JF, KS, JH) and NSW Ministry of Health (JH), and LRJ is a member of the governing board of the Bureau of Health information; research results may inform evaluation/performance measurement for the Department of Health and Bureau of Health Information.

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Contributors

TLJ conceived the study, undertook the literature review, implemented the regression models, conducted descriptive analyses and wrote the first draft. JK provided important intellectual contributions to study design and led the statistical and descriptive analyses. MOF produced some of the regression predictors, contributed substantively to the analysis and intellectual content, and provided detailed revisions throughout the article drafting process. JH conducted analyses and critically reviewed the methodology sections

of the paper. KS, LRJ and JF served as project mentors, providing significant ideas to the development of the model and important intellectual content throughout the draft revision process. All authors have read and approved the final version of the manuscript.

Transparency declaration

I, Tracy L. Johnson (corresponding author), affirm that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned have been explained.

Data Sharing

The patient level data from 45andUp Survey are available to researchers according to its governance framework. See https://www.saxinstitute.org.au/our-work/45-up-study/for-researchers/ for further details.

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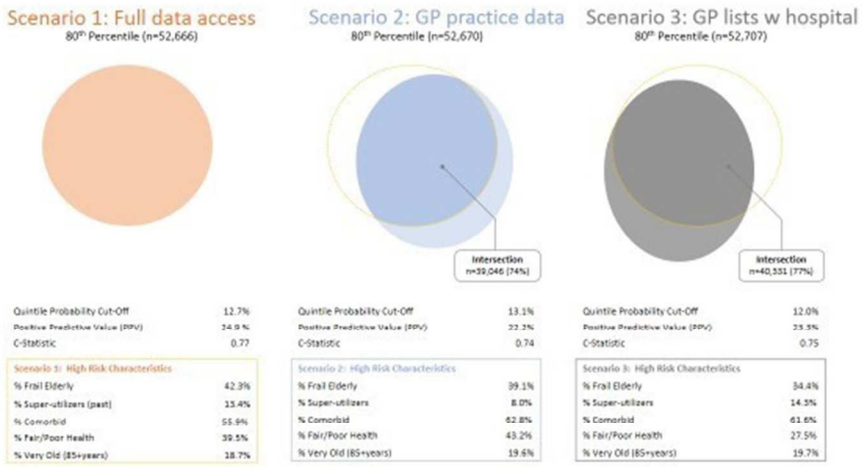

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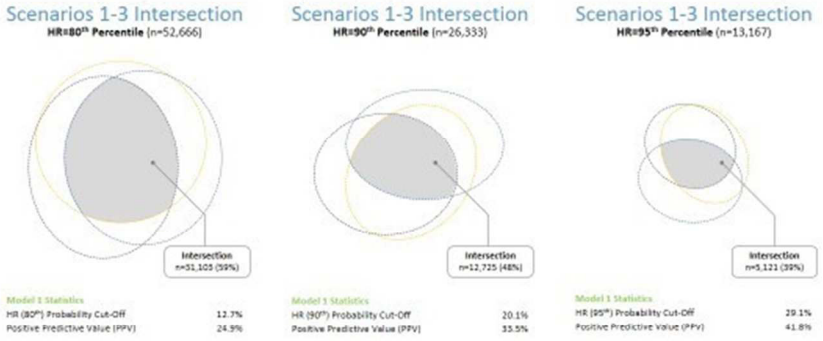

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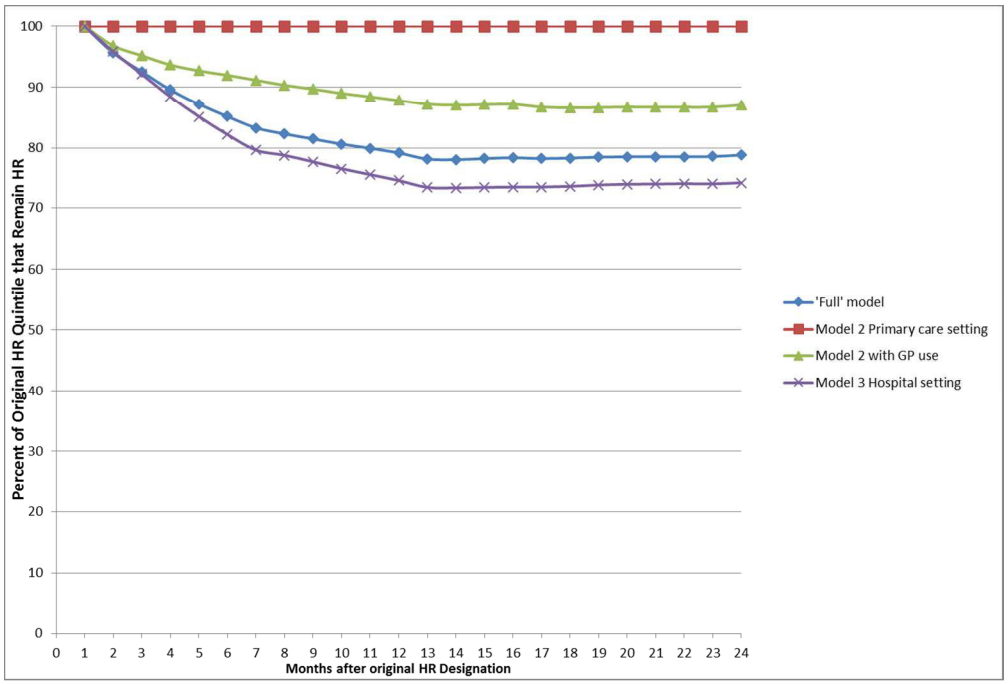

Appendix A: Comparison of predictive risk models under consideration in Australia

PRM Features	NSW Stage 1: Ontario-HARP[i] (complex)	Commonwealth Stage 1: Qadmissions[ii]	Commonwealth Stage 2: Chronic Condition Risk Calculator: "Victoria HARP"	Consolidated List of Available Predictor Variables
Design Elements				
Required data sources	**Hospital EHR**	**GP practice management & hospital EHR**	**GP practice management & assessment data**	**APDC, EDDC, MBS, 45andUp survey, mortality**
Unit of Analysis	**discharge**	**person**	**person**	**Person**
Cohort definition	acute discharges	primary care population	primary care population (for Commonwealth application)	45and Up Survey respondents (with a MBS, EDDC, or APDC linked record)
Prediction Period	**15 mos post-index discharge**	**2 years post index time**	**12 mos post assessment**	**12 mos post index time**
Prediction Outcome	acute presentation (readmission)	1+ emergency admissions	acute presentation	1+ acute, emergency admits
Covariates Used				
Number and types covariates in final model	9 (complex model)	14	21	26 (to test)
SOCIODEMOGRAPHICS				
Age	✓	✓	x	✓
Gender	x	✓	x	✓
Income/Income Decile	x	x	✓	✓
Index of relative SES disadvantage	x	✓	x	✓
Remoteness/Rurality	x	✓ (n=10 regions)	x	✓
Ancestry/Race/Ethnicity	x	✓	x	✓
Aboriginal/Torres Strait Islander	x	x	✓	✓
Language other than English	x	x	✓	✓
Transportation	x	x	✓	X
Housing stability	x	x	✓	X
Asthma triggers	x	x	✓	X
SOCIAL SUPPORT				
Marital status	x	x	x	✓
Caregiver / Other Social Support	x	x	✓	✓
HEALTH STATUS				
Comorbidity Score/Count	✓	x	x	✓
Specific conditions (DX)	✓ (n=19)	✓ (n=12)	✓ (n=7)	✓ (tested, not used)
Illness Severity/Resources Intensity	✓	x	x	x
Specific medications/ polypharmacy/regimen changes	x	✓ (n=5)	✓ (n=2)	✓
Clinical indicators (lab values, PX, etc.)	x	✓ (n=3)	✓	x
Mental illness	x	✓	✓	✓
Drug use/abuse	x	x	✓	x
HEALTH-RELATED BEHAVIORS				
BMI	x	✓	✓	✓
Smoking status	x	✓	✓	✓
Alcohol use	x	✓	✓	✓
Physical Activity	x	x	✓	✓ (tested, not used)
Readiness to Change	x	x	✓ (n=7)	x
FUNCTIONAL STATUS				
Self-reported health status	x	x	x	✓
Health-Related Quality of Life (functional status, disability, self-care)	x	x	✓	✓
Other measures of functional status (mobility, fall history, pain, cognitive impairment, frailty)	x	✓ (falls)	✓ (dementia, pain,falls, incontinence)	✓ (falls)

PRIOR HOSPITAL/ED UTILIZATION				
Index Admit LOS	✓	x	x	✓
Discharge disposition	✓	x	x	x
Previous hospitalizations	✓	✓	✓	✓
Admit via ED	✓	x	x	✓
Previous ED use	✓	x	x	✓
ACCESSIBILITY				
GP care	X	x	✓	✓

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Appendix B: Odds ratio estimates for 12-mos hospital readmission predictive risk models†

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
Data Access Assumptions		Hospital, GP practice management and GP use data, Assessment data (functional status, social support, income)	GP patient management data (patient history only, no use data)	GP patient management data (patient history & use data)	Hospital administrative data & GP patient lists (demographics, not practice management data)
Model intercept†		0.06 (0.05—0.07)	0.04 (0.04—0.05)	0.04 (0.04—0.05)	0.07 (0.07—0.08)
DEMOGRAPHICS/SOCIAL DETERMINANTS OF HEALTH					
Age	45-64	reference	reference	reference	reference
	65-84	1.58 (1.53—1.64)	2.09 (2.03—2.16)	1.82 (1.76—1.88)	1.94 (1.88—2.01)
	85+	3.32 (3.13—3.52)	5.37 (5.10—5.66)	4.56 (4.33—4.81)	4.95 (4.70—5.22)
Gender	Male	reference	reference	reference	reference
	Female	0.74 (0.72—0.76)	0.78 (0.76—0.80)	0.76 (0.74—0.78)	0.83 (0.81—0.86)
Annual Household Income	<10,000	reference	-	-	-
	10,000-29,999	0.94 (0.89—0.99)	-	-	-
	30,000-49,999	0.89 (0.83—0.94)	-	-	-
	50,000-69,999	0.82 (0.77—0.89)	-	-	-
	70,000 or more	0.79 (0.73—0.84)	-	-	-
	Do not wish to answer	0.94 (0.89—1.00)	-	-	-
	Missing	1.08 (1.01—1.17)	-	-	-
Accessibility/ Remoteness Index of Australia (ARIA+)	Metropolitan	reference	reference	reference	reference
	Inner regional	1.09 (1.05—1.12)	1.04 (1.00—1.07)	1.11 (1.08—1.15)	1.00 (0.96—1.03)
	Outer/remote /v.remote	1.26 (1.20—1.32)	1.18 (1.12—1.23)	1.27 (1.21—1.33)	1.16 (1.11—1.22)
	Missing	1.33 (1.19—1.49)	1.28 (1.15—1.43)	1.37 (1.22—1.53)	1.21 (1.08—1.35)
Index Relative Socioeconomic Disadvantage (ISRD)	Quintile 1 (Most Disadvantaged)	reference	reference	reference	reference
	Quintile 2	0.95 (0.91—0.99)	0.91 (0.88—0.95)	0.93 (0.89—0.97)	0.89 (0.85—0.92)
	Quintile 3	0.96 (0.92—1.00)	0.89 (0.85—0.93)	0.92 (0.88—0.96)	0.85 (0.81—0.89)
	Quintile 4	0.94 (0.89—0.98)	0.84 (0.80—0.88)	0.88 (0.84—0.93)	0.79 (0.75—0.83)
	Quintile 5 (Least Disadvantaged)	0.94 (0.89—0.98)	0.80 (0.76—0.84)	0.86 (0.82—0.90)	0.72 (0.69—0.76)
	Missing	0.12 (0.07—0.22)	0.08 (0.05—0.15)	0.10 (0.05—0.17)	0.09 (0.05—0.17)
Aboriginal/Torres Strait Islander	No	reference	reference	reference	reference
	Aboriginal or TSI	not published	not published	not published	not published
	Missing	not published	not published	not published	not published
Language other than English	No	reference	reference	reference	-
	Yes	0.89 (0.84—0.93)	0.93 (0.88—0.97)	0.88 (0.83—0.92)	-
SOCIAL SUPPORT					
Married at Baseline	No	reference	reference	reference	reference
	Yes	1.13 (1.10—1.17)	1.21 (1.17—1.24)	1.20 (1.16—1.24)	1.23 (1.19—1.27)
People to Depend on	No one to depend on	reference	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
(Social Support)	1+ people to depend on	1.05 (0.99—1.12)	-	-	-
	Missing	1.15 (1.06—1.25)	-	-	-
HEALTH CONDITIONS					
Comorbidity Score/Count	No Chronic conditions	reference	reference	reference	reference
	1 Chronic condition	1.14 (1.09—1.18)	1.19 (1.15—1.24)	1.15 (1.11—1.19)	1.30 (1.25—1.34)
	2 Chronic conditions	1.33 (1.27—1.39)	1.50 (1.43—1.56)	1.38 (1.32—1.44)	1.78 (1.71—1.85)
	3+ Chronic conditions	1.53 (1.45—1.61)	1.88 (1.78—1.97)	1.68 (1.59—1.77)	2.48 (2.37—2.61)
Polypharmacy	0 Medications	reference	reference	reference	-
	1-4 Medications	1.14 (1.10—1.19)	1.28 (1.23—1.33)	1.18 (1.14—1.22)	-
	5-+ Medications	1.35 (1.27—1.43)	1.75 (1.65—1.86)	1.50 (1.41—1.59)	-
	Missing	1.29 (1.15—1.44)	1.42 (1.27—1.58)	1.34 (1.20—1.50)	-
MENTAL HEALTH					
Mental illness	Neither depression nor anxiety	reference	reference	reference	-
	Self-reported depression or anxiety	1.01 (0.97—1.05))	1.09 (1.05—1.13)	1.04 (1.00—1.08))	-
	Missing	1.10 (1.06—1.15)	1.12 (1.08—1.17)	1.12 (1.07—1.16)	-
HEALTH-RELATED BEHAVIORS					
BMI	Underweight	reference	reference	reference	-
	Healthy weight	0.85 (0.76—0.95)	0.79 (0.71—0.88)	0.81 (0.73—0.91)	-
	Overweight	0.79 (0.71—0.88)	0.72 (0.65—0.81)	0.75 (0.67—0.84)	-
	Obese	0.77 (0.69—0.87)	0.74 (0.66—0.82)	0.76 (0.68—0.85)	-
	Missing	0.85 (0.76—0.96)	0.84 (0.75—0.94)	0.85 (0.76—0.96)	-
Non-smoking	No	reference	reference	reference	-
	Yes	0.79 (0.74—0.83)	0.77 (0.73—0.81)	0.76 (0.72—0.81)	-
	Missing	0.86 (0.72—1.03)	0.93 (0.78—1.11))	0.90 (0.76—1.08))	-
Safe alcohol intake	No	reference	reference	reference	-
	Yes	1.06 (1.02—1.10)	1.11 (1.07—1.16)	1.09 (1.05—1.13)	-
	Missing	1.14 (1.04—1.24)	1.33 (1.22—1.45)	1.25 (1.14—1.36)	-
FUNCTIONAL STATUS					
Self-reported health status	Excellent	reference	reference	reference	-
	Very good	1.18 (1.11—1.25)	1.28 (1.21—1.36)	1.24 (1.17—1.32)	-
	Good	1.32 (1.24—1.40)	1.71 (1.61—1.81)	1.57 (1.48—1.66)	-
	Fair	1.61 (1.51—1.73)	2.72 (2.55—2.90)	2.35 (2.20—2.51)	-
	Poor	2.13 (1.94—2.34)	4.76 (4.37—5.19)	3.89 (3.56—4.24)	-
	Missing	1.44 (1.31—1.58)	2.39 (2.20—2.59)	2.09 (1.92—2.27)	-
Health-Related Quality of Life	No limitation	reference	-	-	-
	Minor limitation	0.96 (0.91—1.02)	-	-	-
	Mild limitation	1.10 (1.04—1.16)	-	-	-
	Moderate limitation	1.27 (1.21—1.34)	-	-	-
	Severe limitation	1.66 (1.57—1.75)	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
	Missing	1.31 (1.23—1.39)	-	-	-
Falls History	**0 Falls**	**reference**	-	-	-
	1 Fall	1.07 (1.01—1.12)	-	-	-
	2+ Falls	1.15 (1.10—1.20)	-	-	-
	Missing	1.07 (1.00—1.15)	-	-	-
PRIOR HEALTH SERVICE UTILIZATION					
Previous hospitalization (specify look-back)	**None**	**reference**	-	-	**reference**
	1	0.95 (0.91—1.00)	-	-	0.94 (0.90—0.99)
	2	1.25 (1.16—1.35)	-	-	1.29 (1.20—1.39)
	3+	2.23 (2.03—2.45)	-	-	2.44 (2.22—2.68)
Previous ED use (specify look-back)	**None**	**reference**	-	-	**reference**
	1	1.66 (1.58—1.74)	-	-	1.80 (1.71—1.89)
	2	2.13 (1.96—2.32)	-	-	2.39 (2.20—2.60)
	3	2.18 (1.88—2.53)	-	-	2.54 (2.20—2.94)
	4+	3.24 (2.73—3.84)	-	-	3.79 (3.20—4.48)
Prior acute admission via ED	**Not via ED**	**reference**	-	-	**reference**
	All episode in ED	1.23 (1.11—1.36)	-	-	1.20 (1.08—1.32)
	Admitted via ED	1.28 (1.20—1.37)	-	-	1.26 (1.18—1.35)
	N/S or N/A	0.84 (0.80—0.89)	-	-	0.73 (0.69—0.77)
	No Admission	0.69 (0.66—0.73)	-	-	0.56 (0.53—0.59)
LOS of prior acute admission	**0-2 days**	**reference**	-	-	**reference**
	3-7 days	1.13 (1.06—1.20)	-	-	1.22 (1.15—1.30)
	8-14 days	1.25 (1.14—1.36)	-	-	1.40 (1.28—1.53)
	15-30	1.18 (1.05—1.32)	-	-	1.40 (1.24—1.56)
	over 30 days	1.16 (0.99—1.37)	-	-	1.30 (1.10—1.53)
PRIMARY CARE ACCESSIBILITY					
Prior GP care	**0 visits**	**reference**	-	**reference**	-
	1-3 visits	0.88 (0.82—0.95)	-	0.80 (0.75—0.86)	-
	4-5 visits	0.99 (0.91—1.06)	-	0.94 (0.87—1.01)	-
	6-11 visits	1.17 (1.09—1.25)	-	1.23 (1.15—1.31)	-
	12+ visits	1.60 (1.49—1.72)	-	2.04 (1.91—2.19)	-

† The intercept estimate is the estimated odds of the outcome (hospital readmission within 12 months) when all predictor variables equal their reference values. All other estimates are odds ratios. Estimates in brackets are 95% confidence intervals.

Table.

Characteristic	Full sample	80% threshold Model 1: Full data access	80% threshold Model 2: Primary care data	80% threshold Model 3: Hospital data	90% threshold Model 1: Full data access	90% threshold Model 2: Primary care data	90% threshold Model 3: Hospital data	95% threshold Model 1: Full data access	95% threshold Model 2: Primary care data	95% threshold Model 3: Hospital data	Model 1-3 intersection 80% threshold	Model 1-3 intersection 90% threshold	Model 1-3 intersection 95% threshold
SUMMARY STATISTICS													
n (Sample size)	263,328												
n (HR group size)		52,666	52,670	52,707	26,333	26,333	26,372	13,167	13,173	13,189	31,103	12,725	5,121
% (Model agreement)											59	48	39
n (Patients readmitted to hospital)	23,966	13,132	11,712	12,306	8,834	7,451	8,153	5,503	4,508	5,205	8,991	4,851	2,453
HR group probability cut-off		12.7	13.1	12.0	20.1	19.1	18.2	29.1	25.9	26.8			
Positive predictive value (PPV)		24.9	22.2	23.3	33.5	28.3	30.9	41.8	34.2	39.5	28.9	38.1	47.9
Sensitivity		54.8	48.9	51.3	36.9	31.1	34.0	23.0	18.8	21.7	37.5	20.2	10.2
C-statistic (overall)		0.77	0.74	0.75	0.77	0.74	0.75	0.77	0.74	0.75			
SPECIAL POPULATIONS													
Frail elderly [1]	11.2	42.3	39.1	34.4	54.1	52.5	42.1	61.6	62.9	49.1	50.1	63.5	72.5
Multi-morbid (2+ conditions)	23.8	55.9	62.8	61.6	61.7	69.3	62.7	65.0	73.4	68.6	69.6	72.1	78.3
Fair/poor self-reported health	13.3	39.5	43.2	27.5	48.1	58.0	32.5	53.7	65.9	37.6	42.7	54.4	64.1
Super-utilizers[2]	3.6	13.4	8.0	14.3	20.6	9.6	22.3	30.1	11.1	31.9	13.1	18.7	25.3
Died in prediction year	1.1	4.4	3.9	4.2	6.9	5.6	6.4	9.9	7.6	9.3	5.7	8.8	12.7
SELECT RISK FACTORS													
Age (years)													
45-64	58.3	16.4	10.9	12.0	12.7	7.0	9.7	10.6	4.3	7.1	5.2	3.5	2.3
65-84	37.7	64.8	69.5	68.2	58.7	58.3	58.6	53.7	45.4	54.2	63.4	44.8	34.1
85+ years	4.0	18.7	19.6	19.7	28.6	34.7	31.7	35.7	50.3	38.7	31.4	51.7	63.5
Male	46.1	54.8	57.1	56.3	55.5	56.9	56.4	56.4	55.9	56.3	57.0	56.2	56.5
Annual income <$30,000	29.0	53.2	53.1	50.3	54.7	55.9	52.6	55.1	56.5	53.7	55.5	56.3	56.7

Remoteness: outer/remote/ very remote	11.2	13.3	13.8	14.0	13.2	13.5	13.5	12.5	13.1	12.2	13.7	13.2	12.6
Most disadvantaged (IRSD)	20.8	31.9	33.6	32.9	33.3	35.7	34.3	34.0	36.7	35.7	34.9	36.9	38.4
Non-English speaker	9.5	9.8	9.7	8.9	9.8	10.1	9.5	9.8	10.7	9.6	9.5	10.0	10.6
Indigenous													
Not married	30.5	44.0	45.7	44.2	47.9	50.8	49.4	50.4	56.1	52.3	49.2	55.7	60.0
Socially isolated	6.3	6.9	7.4	6.4	7.0	7.7	6.6	7.2	7.8	6.4	6.7	6.9	7.3
# chronic conditions													
0	41.1	14.4	11.0	12.4	12.0	8.5	10.4	10.3	7.3	9.3	9.2	6.6	5.2
1	35.1	29.7	26.2	26.0	26.2	22.2	26.9	24.6	19.2	22.1	21.2	21.3	16.5
Heart disease	11.7	30.3	33.3	32.0	35.5	39.7	35.0	38.9	44.5	39.3	38.8	43.7	49.1
High blood pressure	35.5	55.9	61.2	59.9	57.3	63.0	59.5	58.1	64.3	61.5	63.1	62.5	64.8
Cancer (excluding skin cancers)	15.6	27.9	29.6	32.3	29.8	32.1	33.1	31.4	33.8	35.1	34.0	35.2	38.1
Stroke	3.1	9.9	10.5	10.1	12.7	13.9	11.8	14.7	16.7	14.6	13.4	16.4	20.3
Diabetes	8.9	20.6	23.7	21.5	23.2	27.5	22.2	24.1	29.4	24.0	25.5	26.7	28.6
Blood clot	4.6	10.5	10.8	11.0	12.0	12.6	11.8	13.4	14.0	13.6	12.9	14.2	16.4
Asthma	12.6	18.0	18.9	18.9	19.3	20.6	18.8	20.5	22.1	20.1	20.2	21.1	23.6
Parkinson's disease	0.6	1.8	1.9	1.8	2.3	2.6	2.0	2.8	3.0	2.5	2.3	2.9	3.5
# medications													
0	35.8	10.5	7.7	13.8	8.7	6.0	12.4	7.8	4.8	11.1	7.5	6.0	4.4
1-4	57.6	69.6	70.1	69.6	66.4	63.7	68.7	64.1	59.4	67.5	67.9	64.1	60.7
5+	5.1	18.1	20.5	15.3	23.1	28.5	17.4	26.3	34.1	19.9	22.9	28.0	33.2
Missing	1.5	1.7	1.8	1.4	1.8	1.8	1.5	1.8	1.7	1.5	1.7	1.9	1.7
Depression or Anxiety	16.3	19.5	19.6	16.0	20.2	20.7	16.3	20.4	21.3	16.2	17.7	18.3	19.1
Body mass index													
Underweight	1.2	2.3	2.4	1.8	2.9	3.1	2.1	3.3	3.9	2.3	2.5	3.2	3.8
Obese	20.7	23.7	23.9	22.2	22.5	22.9	20.6	21.3	20.8	19.9	22.4	19.3	17.8
Smoker	7.1	8.7	8.9	5.3	8.4	8.5	5.2	8.1	7.9	5.0	6.1	5.4	5.5

Unsafe alcohol intake	18.4	15.1	14.8	17.1	13.7	12.5	15.2	12.6	10.6	14.1	14.2	11.7	9.9
Self-reported health													
Excellent/very good	50.6	16.6	10.9	28.5	12.3	7.4	23.9	10.1	4.5	20.1	12.2	8.5	4.9
Good	32.6	37.3	38.3	39.2	32.6	27.1	38.1	29.3	21.8	36.4	38.4	29.5	23.2
Missing	3.5	6.6	7.7	4.8	6.9	7.5	5.5	7.0	7.8	5.9	6.8	7.5	7.8
Severe functional limitation	13.4	45.5	39.3	32.3	56.3	51.5	39.6	63.1	60.6	45.8	46.8	59.6	68.7
2+ falls in last 12 months	9.3	21.1	18.3	16.1	25.7	22.4	19.1	29.6	26.3	21.9	21.2	25.9	30.1
# hospitalisations in last 6 months													
0	84.8	62.3	74.1	59.4	50.6	70.9	46.6	37.3	68.3	33.7	62.0	52.5	42.2
1	11.7	24.3	18.0	26.3	28.8	19.5	31.0	32.6	20.5	34.4	24.9	28.8	32.5
# ED visits in last 6 months													
None	91.8	73.1	84.4	71.2	59.7	81.3	56.2	43.3	78.2	39.6	74.3	63.3	49.3
4+	0.3	1.4	0.8	1.4	2.6	1.1	2.7	4.7	1.5	4.9	1.4	2.2	3.9
Admitted to hospital via ED[3]	4.2	17.4	10.9	18.7	28.0	14.3	30.8	41.3	17.9	44.5	18.4	28.9	43.1
1-2 days length of stay[4]	20.4	37.7	28.3	41.4	40.5	28.9	44.2	41.0	28.9	41.5	38.2	39.7	38.3
# previous GP visits in last 6 months													
0	6.5	4.1	4.9	4.6	4.8	6.6	5.9	5.1	8.4	7.1	5.8	8.0	8.9
12+	16.6	52.7	39.1	39.9	62.6	44.8	47.5	69.4	47.9	53.5	49.7	56.6	61.3

[1] Age 65+ years with either severe functional limitations or at least two falls
[2] At least two hospital admissions in last 6 months
[3] Hospitalisations in last 6 months
[4] Last hospitalisation

Scenario 1: Full data access

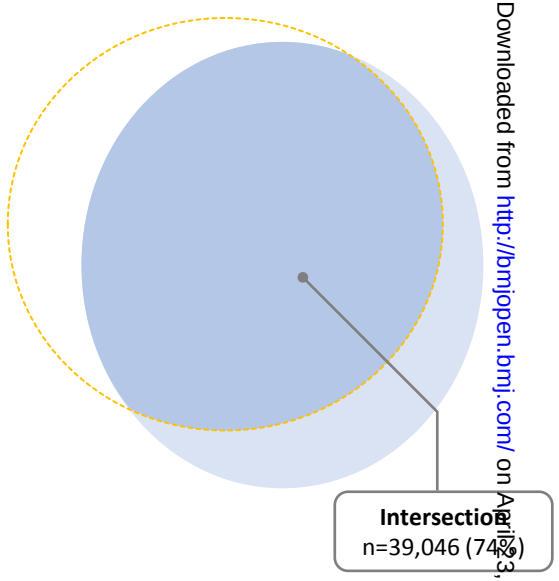
80th Percentile (n=52,666)

Quintile Probability Cut-Off	12.7%
Positive Predictive Value (PPV)	24.9 %
C-Statistic	0.77

Scenario 1: High Risk Characteristics	
% Frail Elderly	42.3%
% Super-utilizers (past)	13.4%
% Comorbid	55.9%
% Fair/Poor Health	39.5%
% Very Old (85+years)	18.7%

Scenario 2: GP practice data

80th Percentile (n=52,670)

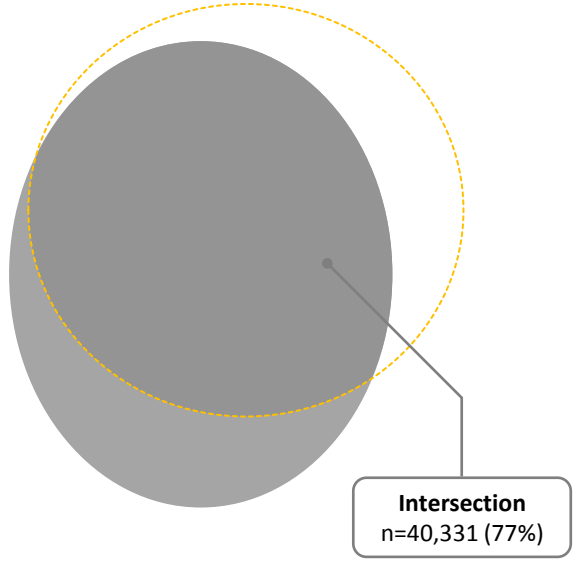


Quintile Probability Cut-Off	13.1%
Positive Predictive Value (PPV)	22.2%
C-Statistic	0.74

Scenario 2: High Risk Characteristics	
% Frail Elderly	39.1%
% Super-utilizers	8.6%
% Comorbid	62.8%
% Fair/Poor Health	43.9%
% Very Old (85+years)	19.6%

Scenario 3: GP lists w hospital

80th Percentile (n=52,707)

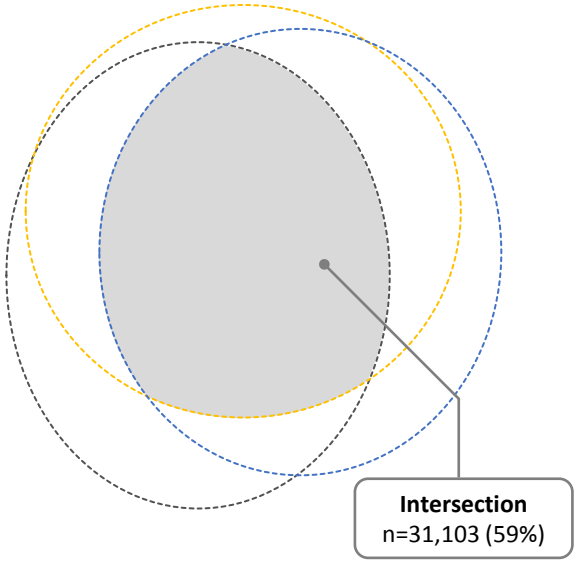


Quintile Probability Cut-Off	12.0%
Positive Predictive Value (PPV)	23.3%
C-Statistic	0.75

Scenario 3: High Risk Characteristics	
% Frail Elderly	34.4%
% Super-utilizers	14.3%
% Comorbid	61.6%
% Fair/Poor Health	27.5%
% Very Old (85+years)	19.7%

Scenarios 1-3 Intersection

HR=80th Percentile (n=52,666)

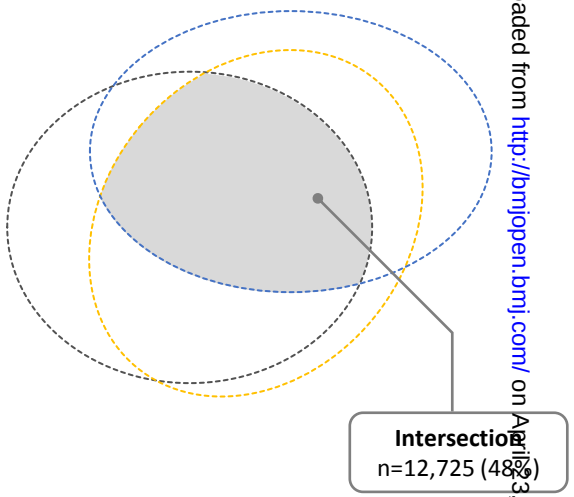


Model 1 Statistics

HR (80th) Probability Cut-Off	12.7%
Positive Predictive Value (PPV)	24.9%

Scenarios 1-3 Intersection

HR=90th Percentile (n=26,333)

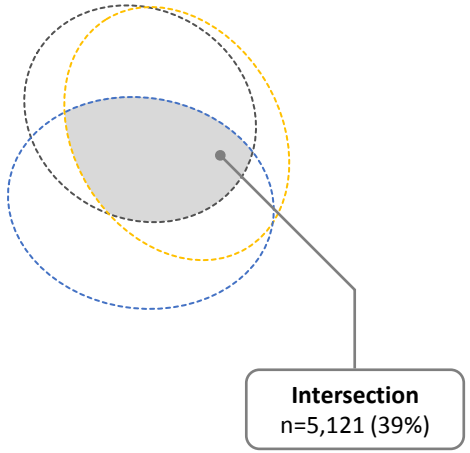


Model 1 Statistics

HR (90th) Probability Cut-Off	20.1%
Positive Predictive Value (PPV)	33.5%

Scenarios 1-3 Intersection

HR=95th Percentile (n=13,167)



Model 1 Statistics

HR (95th) Probability Cut-Off	29.1%
Positive Predictive Value (PPV)	41.8%

STROBE (Strengthening The Reporting of OBservational Studies in Epidemiology) Checklist

A checklist of items that should be included in reports of observational studies. You must report the page number in your manuscript where you consider each of the items listed in this checklist. If you have not included this information, either revise your manuscript accordingly before submitting or note N/A.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Section and Item	Item No.	Recommendation	Reported on Page No.
Title and Abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2-3
Introduction			
Background/Rationale	2	Explain the scientific background and rationale for the investigation being reported	5-6
Objectives	3	State specific objectives, including any prespecified hypotheses	7
Methods			
Study Design	4	Present key elements of study design early in the paper	7-15
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	7-8
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	N/A
		Case-control study—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls	N/A
		Cross-sectional study—Give the eligibility criteria, and the sources and methods of selection of participants	2, 8
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed	N/A
		Case-control study—For matched studies, give matching criteria and the number of controls per case	N/A
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	10-13

Section and Item	Item No.	Recommendation	Reported on Page No.
Data Sources/ Measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	10-13
Bias	9	Describe any efforts to address potential sources of bias	14
Study Size	10	Explain how the study size was arrived at	8,15
Quantitative Variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	10-13
Statistical Methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	14
		(*b*) Describe any methods used to examine subgroups and interactions	14-15
		(*c*) Explain how missing data were addressed	9
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	N/A N/A N/A
		(*e*) Describe any sensitivity analyses	19
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	15
		(b) Give reasons for non-participation at each stage	15
		(c) Consider use of a flow diagram	N/A
Descriptive Data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Appendix C
		(b) Indicate number of participants with missing data for each variable of interest	Appendix C
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	N/A
Outcome Data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	N/A
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	N/A
		Cross-sectional study—Report numbers of outcome events or summary measures	Appendix C

Section and Item	Item No.	Recommendation	Reported on Page No.
Main Results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	15-19
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other Analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	19
Discussion			
Key Results	18	Summarise key results with reference to study objectives	20-24
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	4, 24
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	20-24
Generalisability	21	Discuss the generalisability (external validity) of the study results	4
Other Information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	25

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Once you have completed this checklist, please save a copy and upload it as part of your submission. DO NOT include this checklist as part of the main manuscript document. It must be uploaded as a separate file.

BMJ Open

Predictive Risk Modelling under Different Data Access Scenarios: Who is Identified as High-Risk and for How Long?

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Predictive Risk Modelling under Different Data Access Scenarios: Who is Identified as High-Risk and for How Long?

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Word Count: 4075

ABSTRACT

Objective

This observational study critically explored the performance of different predictive risk models simulating three data access scenarios, comparing: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status over time.

Methods

Cross-sectional health survey data (2006-09) for more than 260,000 Australian adults 45+ years were linked to longitudinal individual hospital, primary care, pharmacy and mortality data. Three risk models predicting acute emergency hospitalisations were explored, simulating conditions where data is accessed through primary care practice management systems, or through hospital based electronic records, or through a hypothetical 'full' model utilizing a wider array of linked data. High-risk patients were identified using different risk-score thresholds. Models were reapplied monthly for 24 months to assess persistence in high-risk categorization.

Results

The three models displayed similar statistical performance. Three-quarters of patients in the high-risk quintile from the 'full' model were also identified using the primary care or

hospital based models, with the remaining patients differing according to age, frailty, multi-morbidity, self-rated health, polypharmacy, prior hospitalisations, and imminent mortality. The use of higher risk prediction thresholds resulted in lower levels of agreement in high-risk designation across models and greater morbidity and mortality in identified patient populations. Persistence of high-risk status varied across approaches according to updated information on utilization history, with up to 25% of patients reassessed as lower-risk within one year.

Conclusion/Implications

Small differences in risk predictors or risk thresholds resulted in comparatively large differences in who was classified as high-risk and for how long. Pragmatic PRM design decisions based on data availability or projected high-risk patient numbers may therefore influence individuals identified as high-risk, overall case-mix, and risk persistence. Routine data linkage would enable greater flexibility in developing and optimizing predictive risk models appropriate to both case-finding and performance measurement applications.

Strengths and Limitations

- This simulation illustrates the extent to which PRMs that rely on different data or modeling specifications will appraise patient risk status differently.
- It also demonstrates how detailed population analyses may augment statistical testing to ensure that PRM algorithms are fit to purpose.
- Linked population and service use data facilitated simulation of several "real world" PRM case-finding and performance measurement applications.
- Simulation findings are intended to be broadly illustrative, not generalizable.
- In practice, case-mix, risk persistence, and high-risk group agreement across alternative PRM applications could differ, due to differences in risk factor availability or measurement, base populations, prediction periods, and other modeling specifications.
- The study population is not representative of NSW, due to oversampling of elderly and rural residents and a low survey response rate (18%) limit.
- Alternatives to conventional logistic regression models (e.g., random effects models or artificial neural networks) were not explored.

INTRODUCTION

To address population health objectives and expenditure growth associated with aging populations and increased chronic disease prevalence, governments and health systems in the UK, Australia, the US and elsewhere are exploring the use of predictive risk modeling (PRM) to better target and integrate services.[1,2,3,4,5] PRM algorithms calculate the probability that a specific patient will experience a future event, such as hospitalisation, based on their unique risk profile. Two different but related applications include identifying individual patients for intervention ("case-finding") and creating high-risk population segments for focused healthcare performance analysis.

Internationally, considerable variability exists in PRM implementations due to differences in health system organization and financing, which affects perceptions of accountability and data access. The entity responsible to administer PRM can be hotly debated, as exemplified by the UK's shift from a centrally-administered algorithm to practice-specific adaptations.[6] PRM requires access to detailed, patient-level risk factor and health service information, ideally, across clinical and community settings and over time. However, for many countries data are non- or partially-linked. Although important to intervention design, limited comparative information exists regarding high-risk patient characteristics identified in different data environments.[7]

A number of review studies compare alternative PRMs with focus on predictive statistics rather than resultant patient profiles and risk persistence.[8,9,10,11,12] Validation studies of

specific instruments also focus on statistical performance, with some also estimating future per-person spending of identified high-risk patients.[13,14,15,16] Billings et al. (2013) is one of the few studies to quantify gains in prediction performance of a hospital-oriented PRM through sequential addition of emergency, outpatient, and general practice information. They also observe that PRMs using non-hospital data identified more lower-acuity patients which could present earlier intervention opportunities.[17] Two studies have found that high-risk population subgroups differ according to the persistence of high-risk status over time.[18,19]

Australia's planned use of PRM in state and national trials provides an opportunity to examine patient profiles under different data access scenarios. For example, the Commonwealth's health care homes initiative will employ an automated PRM using GP data to identify primary care patients who are at-risk of hospitalisation and assess them for allied health service needs and develop multidisciplinary care plans.[20] In parallel, NSW Health will implement an integrated care initiative that will use a hospital algorithm to identify recently discharged patients who need similar supports.[21] Both programs will require that GPs use a standardized care clinical screening tool to determine eligibility for specific services. Despite patient identification efforts that rely on different PRMs using different combinations of GP data, hospital data, and patient survey data, both programs focus on enhanced outpatient care provision to high-risk patients. The likelihood of patient overlap in separately-administered high-risk patient identification efforts is unknown.

This research critically explored the comparative patient identification performance of different PRM algorithms, simulating three common data access scenarios: a 'full' model using all available information, a primary care data only ("GP") model, and a hospital data only ("hospital") model. Using models that draw elements from planned Australian PRMs and patient assessment tools, we assessed: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status.

METHODS

Data Sources

The PRMs used population survey and linked health administrative data for participants in the 45 and Up Study. The Sax Institute's 45 and Up Study is drawn from the population of the state of New South Wales (NSW), Australia. Prospective participants were randomly sampled from the Department of Human Services (formerly Medicare Australia) enrolment database, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. A total of 266,942 participants 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. With approximately 18% of those invited responding, participants represent about 11% of the NSW population aged 45 years and older.[22]

This analysis also incorporated information about respondents' health service use and mortality, obtained with patient consent from administrative health databases and linked to their survey responses. This included public and private sector hospital separation and ED presentation information from the NSW admitted patient and emergency department data collections (APDC and EDDC). It also included information about subsidized general practice (GP) care from the Medicare Benefits Schedule (MBS) and prescription drug use form the Pharmaceuticals Benefits Scheme (PBS). Fact of death information was obtained from the NSW Registry of Birth Deaths and Marriages (RBDM).

The Sax Institute used a unique identifier provided from the Australian Department of Human Services to link survey responses to the MBS and PBS that the Department of Human Services (DHS) provided. Using probabilistic methods, the Centre for Health Record Linkage conducted the data linkage of APDC, EDDC and RBDM datasets.

Cohort definition

We created a NSW cross-sectional, population-based cohort (n=263,328) that includes both primary care users as well as those with recent hospitalisations, as these are common target populations in medical home and integrated care initiatives, including those in Australia.

Prediction Outcome and Prediction Period

The PRM algorithms estimated each respondents' probability of experiencing one or more acute emergency admissions during Fiscal Year 09/10. High-risk patients were

identified as those in the highest quintile (top 20%) of predicted probabilities of hospitalisation. Alternative high-risk thresholds – i.e., the top 5% or 10% -- were also examined.

Predictor and descriptive variable definitions

A consolidated list of predictor variables was drawn from tools in use in the Australian integrated care and health care homes trials, which included a validated Canadian PRM that uses hospital data only, a UK PRM that includes GP data, and an Australian-developed clinical assessment tool.[23,24,25,26] (See Appendix A.) Where data limitations prevented matching measure specifications from the three tools, variable definitions drew from previous work associating the predictor with hospitalisation.[27,28,29,30] Covariates included self-reported measures from the 45 and Up Study (including socio-demographics, social support, health status, health behaviors, and functional status) as well as utilization history from the APDC, EDDC and MBS datasets. (See Table 1.) Missing survey responses were included as discrete values under the assumption that programs would likely attempt to estimate risk for patients with missing information, rather than exclude them from consideration for services. Predictor variables were used as PRM covariates and as descriptive variables to characterize the resultant high-risk populations. Additional analysis variables identifying clinical subgroups were created by collapsing or combining PRM predictors.

Table 1: Variables used in predictive risk models

	Model 1 'Full' model	Model 2 Primary care setting	Model 3 Hospital setting	Sensitivity Analysis: Model 2 with GP use
Sociodemographics/Social support				
Age, gender, Aboriginal status, geographic remoteness, SES, marital status	X	X	X	X
Language spoken at home	X	X	-	X
Income, social isolation	X	-	-	
Health status and health behaviours				
Health condition count*	X	X	X	X
Self-rated health*, polypharmacy, anxiety/depression, BMI, smoking status, unsafe alcohol use	X	X	-	X
Functional status, falls	X	-	-	
Prior health service utilisation				
Previous hospitalisations, admission via ED, length of stay of previous hospitalisation, previous ED use	X	-	X	-
Primary care accessibility				
GP use	X	-	-	X
Total number of variables	**23**	**14**	**11**	**15**

Data Note: The survey variables "health condition count" and "self-rated health" were used to approximate the patient health history information that is commonly captured in GP practice management software.

Socio-Demographics and Social Support Predictors

Socio-demographic and social support variables (age, gender, indigenous status, marital status, language, geographic remoteness, socioeconomic status, income, and social isolation) were obtained from the baseline questionnaire. Using birth date, baseline age was updated to reflect respondent age during prediction and subsequent measurement periods. Quintiles of socioeconomic status were derived from residential postcode using the Australian Bureau of Statistics (ABS) Index of Relative Socioeconomic Disadvantage

(SEIFA IRSD).[31] Similarly, the ABS Accessibility Remoteness Index of Australia Plus (ARIA+) was used to classify remoteness into major city, inner regional, outer regional, remote and very remote categories.[32] Indigenous status (yes/no) included those who self-identified as Aboriginal or Torres Strait Islander, or both. Income was based on *"usual yearly household income before tax, from all sources"* and categorized into $10K increments through $70K. Social isolation was identified as a response of "no one" to a survey question that asked, *"how many people outside your home, but within one hour of travel, do you feel you can depend on or feel very close to?"*

Health Status and Health Behaviours Predictors

To ensure consistency in covariate measurement across the three PRM models, all health status and health behavior measures were calculated from the baseline survey even when also available in administrative data. Several predictors consisted of risk factor counts. The health condition count summed self-reported chronic conditions (0, 1, 2, 3+) according to participants' responses to the questions "*Has a doctor ever told you that you have ...*?" or "*In the last month have you been treated for ...?"* The eight conditions counted were: heart disease, diabetes, high blood pressure, stroke, blood clots, cancer, asthma, or Parkinson's disease. The depression/anxiety measure (yes/no) was also derived from these same questions. The polypharmacy variable totaled the number of medications (0, 1-4, 5+) that respondents had "*taken most of the last 4 weeks*", as selected from a list of common medications. The falls count (0,1,2+) was based on the question, "*during the past 12 months, how many times have you fallen to the floor or the ground?*"

Additional predictors were derived from validated items or short standardised scales included in the 45 and Up baseline questionnaire. Self-rated health (SF-1) was reported as excellent, very good, good, fair or poor. The Body Mass Index (BMI) was collected in Kg/M^2 and responses were classified as underweight (<18.5), normal weight (18.6-25), overweight (26–30), and obese (>30). The question "*are you a regular smoker now?*" was used to assess baseline smoking status. Alcohol use was estimated from self-reports of *"about how many alcoholic drinks do you have each week?"* with unsafe use defined as more than 14 per week (adjusted for 9% under-reporting).[33] Functional capacity was defined according to the Medical Outcomes Study, Short Form 36 Physical Functioning Scale scores, with no limitation corresponding to a score of (100), minor limitation (95–99), mild (85-94), moderate (60–84) and severe limitation (0–59).[34]

Prior Hospital/ED Utilization and Primary Care Accessibility

APDC, EDDC and MBS administrative datasets were used to calculate prior utilization predictors. Variable specifications for the hospitalisation-related covariates were based on the Ontario HARP. Utilization predictors included: acute admission six months prior (0,1,2,3+), length of stay of prior acute admission (0-2, 3-7, 8-14, 15-30, 31+), admission via emergency department (yes/no), emergency department visits six months prior (0,1,2,3,4+). GP visits in the prior twelve months were also calculated and classified as (0, 1-3,4-5, 6-11, 12+).[35] Look-back periods for prior hospital, ED, and GP service use were calculated from the start of the prediction period (July 1, 2009.)

Population Subgroups

Frail elderly were defined as individuals 65+years that reported severe physical limitations and/or 2 or more falls in the last year.[36] Super-utilizers were those with 2+ acute admissions in the previous 6 months. Fair/poor health indicates those whose self-rated health was fair or poor and multi-morbid individuals were those with 2+ health conditions. Those who died during the prediction year are classified as end-of-life. Although these subpopulations were selected because they are often considered clinically distinctive, they are not mutually exclusive designations.

PRM Modeling Scenarios

Three PRM models were developed to simulate high-risk population identification within alternative data environments. These simulations used a combination of service use and population survey data to approximate data commonly captured through hospital EHRs, GP practice management systems, and clinical assessment tools.

PRM-1 ("full model") was built with comprehensive, linked data and used the full, consolidated list of predictor variables to define high-risk status. In addition to data elements routinely available in GP and hospital settings, it included less-commonly collected risk factors such as income, social isolation, and functional status. PRM-2 ("GP model") simulates a primary care-based implementation. Based on the capabilities of the

most common practice management software in Australia, GPs were assumed to have electronic access to socio-demographics, language, health/mental health status, and health behaviours. Conversely, the GP model did not include prior hospitalisation, ED or GP visit information because common GP practice management software does not track utilization history. While practices often have separate business software that includes GP visits, only very sophisticated practices have the data skills to link business information and clinical information for analysis. We did, however, conduct sensitivity analyses on our decision to exclude past GP use via a GP+ model that included GP utilisation. Finally, PRM-3 ("hospital model") assumed that primary care patient rosters were matched with hospital administrative data, providing access to patient demographics, health status, as well as past hospital and ED use. This data matching assumption reflected actual practice in Australia's integrated care pilot and ensured consistency in the base population across the three PRM test scenarios. (See Table 1 for model-specific risk predictors).

All models used a logistic regression to predict the outcome of any acute emergency hospitalisation in Fiscal Year 09/10. The extent to which high-risk individuals were admitted to hospital as predicted (positive predictive value) was assessed and the c-statistic was calculated.[37] All statistical analyses were performed in SAS version 9.4 (SAS Institute Inc., Cary, NC, USA).

Descriptive Analysis and Assessment of Persistence

We compared case-mix, identification consistency, and risk persistence among the high-risk populations identified by each model. High-risk persistence refers to the proportion of high-risk individuals that continue to be (or re-achieve) high-risk status. To assess the persistence, we identified individuals in the high-risk quintiles for four models. Two GP models were included in this analysis, with and without GP utilization history as a predictor variable. We recalculated the risk quintile of these high-risk people on a monthly basis over a two-year period, applying updated age and utilization risk factor information. All other risk predictors were measured at solely baseline, so are not time-varying covariates. Individuals who died during the prediction period were removed from this analysis in the month of their death.

Ethics

The 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC). Additionally, this research, inclusive of data linkage, was approved by the NSW Population and Health Services Research Ethics Committee (HREC/15/CIPHS/42, 04/10/16).

RESULTS

Of the 266,942 participants in the 45 and Up Study, n=266,519 were eligible for inclusion because they used a hospital/ED/medical/pharmacy service between July 2006-

June 2009. Of these, n=3182 were excluded as they died prior to the 1-year prediction period (June 30, 2009). An additional n=9 were excluded for possible linkage errors, leaving 263,328 patients for analysis. Characteristics of the full population is provided in Appendix B.

The probability threshold for the high-risk quintiles were low for all models (12.0 - 13.1%). Approximately one-quarter (22.2-24.9%) of patients in the top risk quintile experienced an emergency admission during the prediction year (positive predictive value) and these high-risk patient admissions represent one-half (48.9-54.8%) of total admissions (sensitivity). Statistical performance of the three PRM scenarios was very similar, with moderately strong c-statistics for all models, ranging .74 to .77.

Despite similarities in predictive accuracy, the three PRM scenarios yielded different high-risk individuals and population characteristics (Figure 1).

Sharing three-quarters (74%) of patients in common with the full model, the primary care model high risk group includes more multi-morbid individuals (62.8% vs. 55.9%) and those in fair/poor health (43.2% vs. 39.5%) but fewer super-utilizers (8.0% vs. 13.4%) and those at the end-of-life (3.9% vs. 4.4%). The hospital high-risk quintile also agreed with the full model one three quarters of the time (77%). Across the three models, the hospital high-risk group includes the lowest proportion of frail elderly (34.4% vs. 42.3%) and those in fair/poor health (27.5% vs. 43.2%) and highest proportion of super-utilizers

(14.3% vs. 8.0%). These case mix differences across high-risk quintiles are driven by differences among the one-quarter of patients not shared in common. (See Figure 2.)

Nearly two-thirds (59%) of the top quintile of high-risk individuals were consistently identified within all three models (see Figure 2). As compared to the full model, this overlap group has higher morbidity and mortality: with multi-morbid individuals (69.6% vs. 55.9%), frail elderly (50.1% vs. 42.3%) in fair/poor health (42.7% vs. 39.5%) and very old (31.4% vs. 18.7%). They are also somewhat more likely to be at the end of life (5.7% vs. 4.4%). As the high-risk threshold is increased to the 90th or 95th decile, positive predictive values increase in the range of 28.3-33.5 and 34.3-41.8 respectively, but the models' intersection decreases, falling to 48% and 39% shared patients, respectively. This results primarily from the GP model diverging from the other two. (Appendix B.)

Table 2 summarizes the extent to which characteristics of the high-risk patient cohort changed when using different models or risk prediction thresholds. High-risk group acuity increased dramatically as high-risk thresholds increased. Proportions of very old, frail elderly, multi-morbid individuals, super-utilizers and those who report fair/poor health increased by more than 10 percentage points. With the exception of age and marital status, there was little change (<5 percentage points) in the sociodemographic and behavioral profile of high-risk patients, irrespective of model or high-risk threshold. Although not all population characteristics were explicitly measured in all models (See Figure 1), this did not consistently affect their prevalence in high-risk groups. For example, functional status was measured explicitly only in the full model, but individuals

with severe functional limitations accounted for at least one-third of high-risk quintile patients (32.3-45.5%) across models. In general, patient characteristics with high odds ratios (>1.3) were the most sensitive to modeling specifications. (See Appendix C for odds ratios and Appendix B for selected case-mix characteristics by model and threshold.)

Table 2: Variability in case mix among patients identified as 'high risk' when varying modelling approach or high risk admission thresholds

	Case Mix Changes: Average percentage point spread between minimum and maximum population proportions					
	Same Threshold, Different models "Model Effect"			Same Model, Different Thresholds "Threshold Effect"		
	<5	5-10	>10	<5	5-10	>10
Frail Elderly			X			X
Super-Utilizers (Hospital, ED, GP)			X			X
Individuals reporting Fair/Poor Health			X			X
Very Old (85+ years)		X				X
People taking 5+ Medications			X		X	
Individuals reporting Excellent/Very Good Health			X		X	
Multi-Morbid Individuals		X			X	
Middle-Aged Adults (45-64 years)		X			X	
People at End-of-Life	X			X		
Unmarried Persons	X				X	
Persons with Depression/Anxiety	X			X		
Socio-demographic Groups (Males, Low-Income, Residents of Most Disadvantaged Areas, Rural Residents Non-English Speakers)	X			X		

Figure 3 illustrates that four in five (78.8%) high-risk individuals for the full model and three of four (74.3%) in the hospital model remain persistently high-risk when re-evaluated over a two-year period. For these models, approximately 20-25% of high-risk group members gradually lose high-risk status throughout the first year following identification. High-risk group membership stabilizes thereafter.

Reduction in risk status results from individuals no longer meeting the "prior ED" or "prior hospitalisation" criteria, which are used to assess risk in the full and hospital models. By contrast, all of the GP high-risk quintile (100%) remained persistently high risk, because only age changed over the two-year period. Unlike the other two models, the GP model did not include prior utilization history, and all other risk factors were measured solely at baseline. While advancing age increases risk status, this analysis focuses on individuals already at highest risk. As a result, for a fixed survey cohort, high-risk status did not vary over time. In the GP+ model that included GP usage history, 12.9% of high-risk individuals identified with the GP+ model lost high-risk status over two years.

DISCUSSION

To effectively leverage PRM as part of the implementation of medical home, integrated care and other quality improvement efforts, stakeholders need to know whether they are targeting the "right" patients and to understand how well health systems are currently performing for them. Who is the "right" patient depends on the clinical or measurement

context. Our study demonstrated sensitivity of case-mix and risk persistence to PRM specifications, resulting in somewhat different target populations with different hospitalisation risks. One cannot rely solely on predictive performance to assess model suitability for either clinical or evaluative purposes.

Among our population-based cohort, all three models resulted in high-risk quintiles that included relatively low cut-points for the risk of admission (12-13%), with one-in-four individuals subsequently hospitalized. The large number of people with lower risk scores meant that the high-risk population was sensitive to varying risk predictors and thresholds. As high-risk thresholds increased, case-mix was increasingly characterized by high proportions of very old, frail elderly, multi-morbid individuals, and those who report fair/poor health. At the 95th percentile, for example, more than one in four high-risk group members had a history of repeat hospitalisations and nearly one in 10 would die during the prediction year. Differences between high-risk groups reflected the strongest PRM predictors, highlighting the need to ensure the modeling specifications are optimized to "find cases" appropriate for the intervention.

Risk status may be conceptualized as something that changes over time (e.g., as an outcome) or it may be thought of as a relatively stable characteristic of a patient or a population. How long a person remained high-risk depended on the PRM's relative reliance on factors that could change over time – only age and recent utilization history in our models. Risk status was least stable in PRMs that incorporated prior hospital use. It is common in clinical settings to have access to both time-variant and -invariant patient

data. Some patient information is regularly updated (e.g., utilization history, age). Other patient data does not typically change (gender, race/ethnicity). Still other information maybe collected once for a specific purpose or infrequently reassessed (e.g., eligibility screening data).

Case Finding Implications

Case-finding PRM applications seek to target interventions by identifying patients at-risk of hospitalisation. Our results demonstrate that fully or partially-linked data identified high-risk patients who would not have been classified as such using GP data alone - for example, super-utilizers with multiple prior hospitalisations. In a general practice setting, such patients may not have been targeted for closer monitoring, especially if they were out-of-care or new to the practice. Sharing actionable information across data settings is a clear value-add and often an explicit motivation for predictive risk modeling.

Whether a patient's high-risk status is relatively more persistent or episodic also has bearing on case-finding. For example, if risk manifests episodically, clinical interventions may be short-term and time-sensitive. To identify new at-risk patients in near real-time, the PRM base population may need to be updated and reassessed more frequently. In practice, not all variables commonly used in PRMs are available on a real-time basis, including those (e.g., hospitalisation history) that influence risk persistence.[38] If data lags

are long, the window of opportunity for intervention may close before providers become aware of a change in risk status.

Performance Measurement Implications

Additional considerations apply for the use of PRM in performance measurement applications. Here, the aim is to define high-risk population segments, for example, to understand how well health systems have been performing for high-risk populations and evaluate the impact of new models of care. PRM-defined population segments could be used to describe the regional distribution of high-risk populations and to assess past and current service use, morbidity, mortality, and other medical home/integrated care outcomes. Fair and appropriate performance measurement therefore requires a reasonable match between target populations identified via case-finding and corresponding performance measurement populations. Yet in our findings, only three-quarters of patients, at best, were commonly identified using data available in different settings. While the minimum degree of agreement necessary for analysis may differ across performance measurement applications – e.g., program evaluation may differ from on-going health system reporting -- it is clear that clinical intervention and performance populations will not be fully equivalent unless they are using exactly the same data.

Even with identical data, pragmatic data analysis decisions could inadvertently introduce bias. For example, case-finding applications often set risk thresholds high due to clinical capacity constraints,[39] while performance measurement applications may prefer larger

risk groups to ensure adequate sample size for analysis. In our simulation, morbidity and mortality dramatically increased as risk thresholds increased. Therefore, creating a larger analysis population by relaxing the PRM high-risk threshold would not only increase sample size (intended), it would also change case-mix (unintended).

Stratified approaches to performance measurement also need to reflect on the persistence of high-risk status relative to the outcome assessment timeframe. Stratified analysis is well-suited for short-term outcomes that are measured soon after patients are classified as high-risk, such as care planning or readmission. However, medical home and integrated care initiatives often aim to reduce long-term hospitalisation rates and costs, measured years later.[40] In our simulation, up to 20% of high-risk patients in the full model and 25% identified via the hospital model would change risk status within a year of identification. From a performance measurement perspective, this means that high-risk patients that become lower risk over time – whether due to usual care or program interventions -- would no longer be counted among the "high-risk" strata for which outcomes are reported, unless methodological steps were employed to retain them.

Theoretically, variation in care could also be reflected in risk status, and persistence of high-risk status could potentially be explored as an outcome of care to be assessed as part of performance measurement. The GP model, with regularly updated risk factor information related to health behaviours and self-rated health, might work well for this purpose. By contrast, the hospital model is highly endogenous, with recent hospitalisation history a key determinant in establishing current (hospitalisation) risk

status. Because risk scores in this instance track with recent hospital use, monitoring hospitalisation patterns may provide a more direct means for benchmarking and evaluating variation in care. Given the predominantly time-invariant variables in our study, we did not attempt to investigate the utility of risk status persistence as an outcome but highlight it as a promising area for future research.

Regional differences may emerge in stratified performance outcomes or in high-risk patients' rates of return to lower risk status. Designing meaningful comparisons of performance across sites will require careful consideration. Within the broader high-risk population segment, case mix is likely to differ by clinical site, especially if they implement PRMs tailored to their populations. Even with a standard PRM, known regional variations in demographics and health status will likely result in some sites having high-risk groups dominated by frail elderly, others by super-utilizers, and still others by the multi-morbid. For certain performance comparisons, it may be necessary to risk-adjust (within risk strata) or further stratify (e.g., by subgroup) to account for this heterogeneity. This area is also ripe for additional research.

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Competing Interests

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Contributors

TLJ conceived the study, undertook the literature review, implemented the regression models, conducted descriptive analyses and wrote the first draft. JK provided important intellectual contributions to study design and led the statistical and descriptive analyses. MOF produced some of the regression predictors, contributed substantively to the analysis and intellectual content, and provided detailed revisions throughout the article drafting process. JH conducted analyses and critically reviewed the methodology sections of the paper. KS, LJ and JFL served as project mentors, providing significant ideas to the development of the model and important intellectual content throughout the draft revision process. All authors have read and approved the final version of the manuscript.

Transparency declaration

I, Tracy L. Johnson (corresponding author), affirm that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned have been explained.

Data Sharing

The patient level data from 45andUp Survey are available to researchers according to its governance framework. See https://www.saxinstitute.org.au/our-work/45-up-study/for-researchers/ for further details.

Copyright

Figure 1: Comparison of High-Risk Quintiles from the Full, GP and Hospital scenarios

Figure 2: Intersection of Models for Different High Risk Thresholds

Figure 3: Persistence of High-Risk Group Status over Time:
% of Original HR Quintile that are High Risk in Subsequent 24 Months

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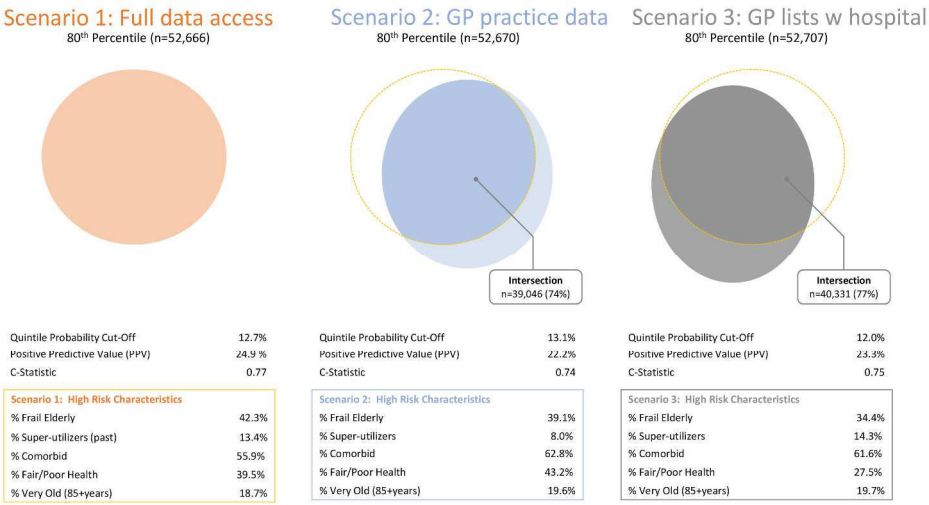

Figure 1: Comparison of High-Risk Quintiles from the Full, GP and Hospital scenarios

273x155mm (300 x 300 DPI)

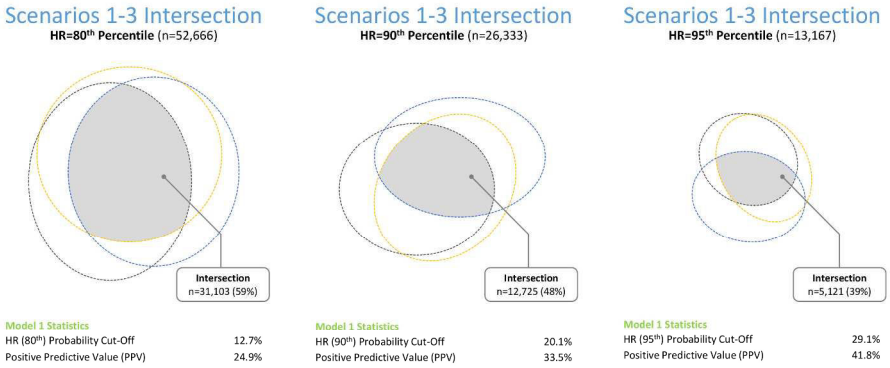

Figure 2: Intersection of Models for Different High Risk Thresholds

273x127mm (300 x 300 DPI)

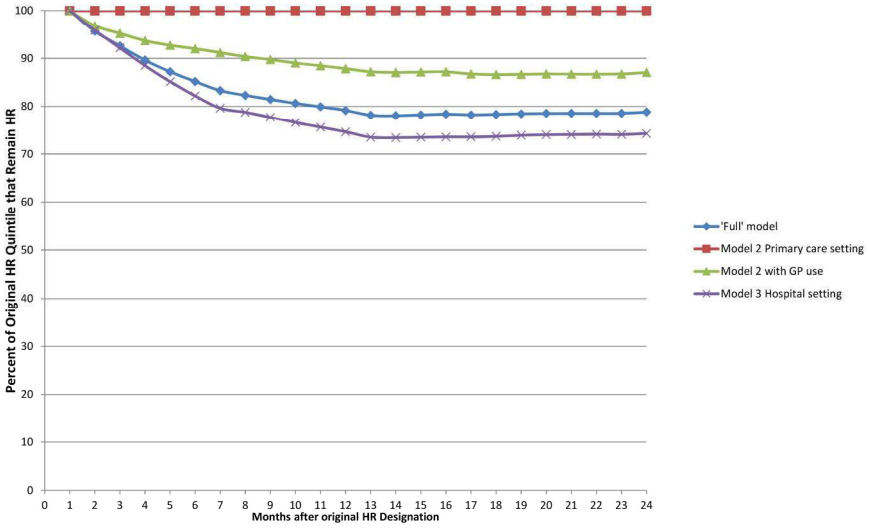

Figure 3: Persistence of High-Risk Group Status over Time:
% of Original HR Quintile that are High Risk in Subsequent 24 Months

199x130mm (300 x 300 DPI)

Appendix A: Comparison of predictive risk models under consideration in Australia

PRM Features	NSW Stage 1: Ontario-HARP[i] (complex)	Commonwealth Stage 1: Qadmissions[ii]	Commonwealth Stage 2: Chronic Condition Risk Calculator: "Victoria HARP"	Consolidated List of Available Predictor Variables
Design Elements				
Required data sources	**Hospital EHR**	**GP practice management & hospital EHR**	**GP practice management & assessment data**	**APDC, EDDC, MBS, 45andUp survey, mortality**
Unit of Analysis	**discharge**	**person**	**person**	**Person**
Cohort definition	acute discharges	primary care population	primary care population (for Commonwealth application)	45and Up Survey respondents (with a MBS, EDDC, or APDC linked record)
Prediction Period	**15 mos post-index discharge**	**2 years post index time**	**12 mos post assessment**	**12 mos post index time**
Prediction Outcome	acute presentation (readmission)	1+ emergency admissions	acute presentation	1+ acute, emergency admits
Covariates Used				
Number and types covariates in final model	9 (complex model)	14	21	26 (to test)
SOCIODEMOGRAPHICS				
Age	✓	✓	x	✓
Gender	x	✓	x	✓
Income/Income Decile	x	x	✓	✓
Index of relative SES disadvantage	x	✓	x	✓
Remoteness/Rurality	x	✓ (n=10 regions)	x	✓
Ancestry/Race/Ethnicity	x	✓	x	✓
Aboriginal/Torres Strait Islander	x	x	✓	✓
Language other than English	x	x	✓	✓
Transportation	x	x	✓	X
Housing stability	x	x	✓	X
Asthma triggers	x	x	✓	X
SOCIAL SUPPORT				
Marital status	x	x	x	✓
Caregiver / Other Social Support	x	x	✓	✓
HEALTH STATUS				
Comorbidity Score/Count	✓	x	x	✓
Specific conditions (DX)	✓ (n=19)	✓ (n=12)	✓ (n=7)	✓ (tested, not used)
Illness Severity/Resources Intensity	✓	x	x	x
Specific medications/ polypharmacy/regimen changes	x	✓ (n=5)	✓ (n=2)	✓
Clinical indicators (lab values, PX, etc.)	x	✓ (n=3)	✓	x
Mental illness	x	✓	✓	✓
Drug use/abuse	x	x	✓	x
HEALTH-RELATED BEHAVIORS				
BMI	x	✓	✓	✓
Smoking status	x	✓	✓	✓
Alcohol use	x	✓	✓	✓
Physical Activity	x	x	✓	✓ (tested, not used)
Readiness to Change	x	x	✓ (n=7)	x
FUNCTIONAL STATUS				
Self-reported health status	x	x	x	✓
Health-Related Quality of Life (functional status, disability, self-care)	x	x	✓	✓
Other measures of functional status (mobility, fall history, pain, cognitive impairment, frailty)	x	✓ (falls)	✓ (dementia, pain,falls, incontinence)	✓ (falls)

PRIOR HOSPITAL/ED UTILIZATION				
Index Admit LOS	✓	x	x	✓
Discharge disposition	✓	x	x	x
Previous hospitalizations	✓	✓	✓	✓
Admit via ED	✓	x	x	✓
Previous ED use	✓	x	x	✓
ACCESSIBILITY				
GP care	X	x	✓	✓

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Population Characteristics by Model and High-Risk Threshhold

Characteristic	Full sample	80% threshold			90% threshold			95% threshold			Model 1-3 intersection		
		Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	80% threshold	90% threshold	95% threshold
SUMMARY STATISTICS													
n (Sample size)	263,328												
n (HR group size)		52,666	52,670	52,707	26,333	26,333	26,372	13,167	13,173	13,189	31,103	12,725	5,121
% (Model agreement)											59	48	39
n (Patients readmitted to hospital)	23,966	13,132	11,712	12,306	8,834	7,451	8,153	5,503	4,508	5,205	8,991	4,851	2,453
HR group probability cut-off		12.7	13.1	12.0	20.1	19.1	18.2	29.1	25.9	26.8			
Positive predictive value (PPV)		24.9	22.2	23.3	33.5	28.3	30.9	41.8	34.2	39.5	28.9	38.1	47.9
Sensitivity		54.8	48.9	51.3	36.9	31.1	34.0	23.0	18.8	21.7	37.5	20.2	10.2
C-statistic (overall)		0.77	0.74	0.75	0.77	0.74	0.75	0.77	0.74	0.75			
SPECIAL POPULATIONS													
Frail elderly [1]	11.2	42.3	39.1	34.4	54.1	52.5	42.1	61.6	62.9	49.1	50.1	63.5	72.5
Multi-morbid (2+ conditions)	23.8	55.9	62.8	61.6	61.7	69.3	62.7	65.0	73.4	68.6	69.6	72.1	78.3
Fair/poor self-reported health	13.3	39.5	43.2	27.5	48.1	58.0	32.5	53.7	65.9	37.6	42.7	54.4	64.1
Super-utilizers[2]	3.6	13.4	8.0	14.3	20.6	9.6	22.3	30.1	11.1	31.9	13.1	18.7	25.3
Died in prediction year	1.1	4.4	3.9	4.2	6.9	5.6	6.4	9.9	7.6	9.3	5.7	8.8	12.7
SELECT RISK FACTORS													
Age (years)													
45-64	58.3	16.4	10.9	12.0	12.7	7.0	9.7	10.6	4.3	7.1	5.2	3.5	2.3
65-84	37.7	64.8	69.5	68.2	58.7	58.3	58.6	53.7	45.4	54.2	63.4	44.8	34.1
85+ years	4.0	18.7	19.6	19.7	28.6	34.7	31.7	35.7	50.3	38.7	31.4	51.7	63.5
Male	46.1	54.8	57.1	56.3	55.5	56.9	56.4	56.4	55.9	56.3	57.0	56.2	56.5
Annual income <$30,000	29.0	53.2	53.1	50.3	54.7	55.9	52.6	55.1	56.5	53.7	55.5	56.3	56.7

Remoteness: outer/remote/ very remote	11.2	13.3	13.8	14.0	13.2	13.5	13.5	12.5	13.1	12.2	13.7	13.2	12.6
Most disadvantaged (IRSD)	20.8	31.9	33.6	32.9	33.3	35.7	34.3	34.0	36.7	35.7	34.9	36.9	38.4
Non-English speaker	9.5	9.8	9.7	8.9	9.8	10.1	9.5	9.8	10.7	9.6	9.5	10.0	10.6
Indigenous													
Not married	30.5	44.0	45.7	44.2	47.9	50.8	49.4	50.4	56.1	52.3	49.2	55.7	60.0
Socially isolated	6.3	6.9	7.4	6.4	7.0	7.7	6.6	7.2	7.8	6.4	6.7	6.9	7.3
# chronic conditions													
0	41.1	14.4	11.0	12.4	12.0	8.5	10.4	10.3	7.3	9.3	9.2	6.6	5.2
1	35.1	29.7	26.2	26.0	26.2	22.2	26.9	24.6	19.2	22.1	21.2	21.3	16.5
Heart disease	11.7	30.3	33.3	32.0	35.5	39.7	35.0	38.9	44.5	39.3	38.8	43.7	49.1
High blood pressure	35.5	55.9	61.2	59.9	57.3	63.0	59.5	58.1	64.3	61.5	63.1	62.5	64.8
Cancer (excluding skin cancers)	15.6	27.9	29.6	32.3	29.8	32.1	33.1	31.4	33.8	35.1	34.0	35.2	38.1
Stroke	3.1	9.9	10.5	10.1	12.7	13.9	11.8	14.7	16.7	14.6	13.4	16.4	20.3
Diabetes	8.9	20.6	23.7	21.5	23.2	27.5	22.2	24.1	29.4	24.0	25.5	26.7	28.6
Blood clot	4.6	10.5	10.8	11.0	12.0	12.6	11.8	13.4	14.0	13.6	12.9	14.2	16.4
Asthma	12.6	18.0	18.9	18.9	19.3	20.6	18.8	20.5	22.1	20.1	20.2	21.1	23.6
Parkinson's disease	0.6	1.8	1.9	1.8	2.3	2.6	2.0	2.8	3.0	2.5	2.3	2.9	3.5
# medications													
0	35.8	10.5	7.7	13.8	8.7	6.0	12.4	7.8	4.8	11.1	7.5	6.0	4.4
1-4	57.6	69.6	70.1	69.6	66.4	63.7	68.7	64.1	59.4	67.5	67.9	64.1	60.7
5+	5.1	18.1	20.5	15.3	23.1	28.5	17.4	26.3	34.1	19.9	22.9	28.0	33.2
Missing	1.5	1.7	1.8	1.4	1.8	1.8	1.5	1.8	1.7	1.5	1.7	1.9	1.7
Depression or Anxiety	16.3	19.5	19.6	16.0	20.2	20.7	16.3	20.4	21.3	16.2	17.7	18.3	19.1
Body mass index													
Underweight	1.2	2.3	2.4	1.8	2.9	3.1	2.1	3.3	3.9	2.3	2.5	3.2	3.8
Obese	20.7	23.7	23.9	22.2	22.5	22.9	20.6	21.3	20.8	19.9	22.4	19.3	17.8
Smoker	7.1	8.7	8.9	5.3	8.4	8.5	5.2	8.1	7.9	5.0	6.1	5.4	5.5

Unsafe alcohol intake	18.4	15.1	14.8	17.1	13.7	12.5	15.2	12.6	10.6	14.1	14.2	11.7	9.9
Self-reported health													
Excellent/very good	50.6	16.6	10.9	28.5	12.3	7.4	23.9	10.1	4.5	20.1	12.2	8.5	4.9
Good	32.6	37.3	38.3	39.2	32.6	27.1	38.1	29.3	21.8	36.4	38.4	29.5	23.2
Missing	3.5	6.6	7.7	4.8	6.9	7.5	5.5	7.0	7.8	5.9	6.8	7.5	7.8
Severe functional limitation	13.4	45.5	39.3	32.3	56.3	51.5	39.6	63.1	60.6	45.8	46.8	59.6	68.7
2+ falls in last 12 months	9.3	21.1	18.3	16.1	25.7	22.4	19.1	29.6	26.3	21.9	21.2	25.9	30.1
# hospitalisations in last 6 months													
0	84.8	62.3	74.1	59.4	50.6	70.9	46.6	37.3	68.3	33.7	62.0	52.5	42.2
1	11.7	24.3	18.0	26.3	28.8	19.5	31.0	32.6	20.5	34.4	24.9	28.8	32.5
# ED visits in last 6 months													
None	91.8	73.1	84.4	71.2	59.7	81.3	56.2	43.3	78.2	39.6	74.3	63.3	49.3
4+	0.3	1.4	0.8	1.4	2.6	1.1	2.7	4.7	1.5	4.9	1.4	2.2	3.9
Admitted to hospital via ED[3]	4.2	17.4	10.9	18.7	28.0	14.3	30.8	41.3	17.9	44.5	18.4	28.9	43.1
1-2 days length of stay[4]	20.4	37.7	28.3	41.4	40.5	28.9	44.2	41.0	28.9	41.5	38.2	39.7	38.3
# previous GP visits in last 6 months													
0	6.5	4.1	4.9	4.6	4.8	6.6	5.9	5.1	8.4	7.1	5.8	8.0	8.9
12+	16.6	52.7	39.1	39.9	62.6	44.8	47.5	69.4	47.9	53.5	49.7	56.6	61.3

[1] Age 65+ years with either severe functional limitations or at least two falls
[2] At least two hospital admissions in last 6 months
[3] Hospitalisations in last 6 months
[4] Last hospitalisation

Appendix C: Odds ratio estimates for 12-mos hospital readmission predictive risk models†

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
Data Access Assumptions		Hospital, GP practice management and GP use data, Assessment data (functional status, social support, income)	GP patient management data (patient history only, no use data)	GP patient management data (patient history & use data)	Hospital administrative data & GP patient lists (demographics, not practice management data)
Model intercept†		0.06 (0.05—0.07)	0.04 (0.04—0.05)	0.04 (0.04—0.05)	0.07 (0.07—0.08)
DEMOGRAPHICS/SOCIAL DETERMINANTS OF HEALTH					
Age	45-64	reference	reference	reference	reference
	65-84	1.58 (1.53—1.64)	2.09 (2.03—2.16)	1.82 (1.76—1.88)	1.94 (1.88—2.01)
	85+	3.32 (3.13—3.52)	5.37 (5.10—5.66)	4.56 (4.33—4.81)	4.95 (4.70—5.22)
Gender	Male	reference	reference	reference	reference
	Female	0.74 (0.72—0.76)	0.78 (0.76—0.80)	0.76 (0.74—0.78)	0.83 (0.81—0.86)
Annual Household Income	<10,000	reference	-	-	-
	10,000-29,999	0.94 (0.89—0.99)	-	-	-
	30,000-49,999	0.89 (0.83—0.94)	-	-	-
	50,000-69,999	0.82 (0.77—0.89)	-	-	-
	70,000 or more	0.79 (0.73—0.84)	-	-	-
	Do not wish to answer	0.94 (0.89—1.00)	-	-	-
	Missing	1.08 (1.01—1.17)	-	-	-
Accessibility/ Remoteness Index of Australia (ARIA+)	Metropolitan	reference	reference	reference	reference
	Inner regional	1.09 (1.05—1.12)	1.04 (1.00—1.07)	1.11 (1.08—1.15)	1.00 (0.96—1.03)
	Outer/remote /v.remote	1.26 (1.20—1.32)	1.18 (1.12—1.23)	1.27 (1.21—1.33)	1.16 (1.11—1.22)
	Missing	1.33 (1.19—1.49)	1.28 (1.15—1.43)	1.37 (1.22—1.53)	1.21 (1.08—1.35)
Index Relative Socioeconomic Disadvantage (ISRD)	Quintile 1 (Most Disadvantaged)	reference	reference	reference	reference
	Quintile 2	0.95 (0.91—0.99)	0.91 (0.88—0.95)	0.93 (0.89—0.97)	0.89 (0.85—0.92)
	Quintile 3	0.96 (0.92—1.00)	0.89 (0.85—0.93)	0.92 (0.88—0.96)	0.85 (0.81—0.89)
	Quintile 4	0.94 (0.89—0.98)	0.84 (0.80—0.88)	0.88 (0.84—0.93)	0.79 (0.75—0.83)
	Quintile 5 (Least Disadvantaged)	0.94 (0.89—0.98)	0.80 (0.76—0.84)	0.86 (0.82—0.90)	0.72 (0.69—0.76)
	Missing	0.12 (0.07—0.22)	0.08 (0.05—0.15)	0.10 (0.05—0.17)	0.09 (0.05—0.17)
Aboriginal/Torres Strait Islander	No	reference	reference	reference	reference
	Aboriginal or TSI	not published	not published	not published	not published
	Missing	not published	not published	not published	not published
Language other than English	No	reference	reference	reference	-
	Yes	0.89 (0.84—0.93)	0.93 (0.88—0.97)	0.88 (0.83—0.92)	-
SOCIAL SUPPORT					
Married at Baseline	No	reference	reference	reference	reference
	Yes	1.13 (1.10—1.17)	1.21 (1.17—1.24)	1.20 (1.16—1.24)	1.23 (1.19—1.27)
People to Depend on	No one to depend on	reference	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
(Social Support)	1+ people to depend on	1.05 (0.99—1.12)	-	-	-
	Missing	1.15 (1.06—1.25)	-	-	-
HEALTH CONDITIONS					
Comorbidity Score/Count	No Chronic conditions	reference	reference	reference	reference
	1 Chronic condition	1.14 (1.09—1.18)	1.19 (1.15—1.24)	1.15 (1.11—1.19)	1.30 (1.25—1.34)
	2 Chronic conditions	1.33 (1.27—1.39)	1.50 (1.43—1.56)	1.38 (1.32—1.44)	1.78 (1.71—1.85)
	3+ Chronic conditions	1.53 (1.45—1.61)	1.88 (1.78—1.97)	1.68 (1.59—1.77)	2.48 (2.37—2.61)
Polypharmacy	0 Medications	reference	reference	reference	-
	1-4 Medications	1.14 (1.10—1.19)	1.28 (1.23—1.33)	1.18 (1.14—1.22)	-
	5-+ Medications	1.35 (1.27—1.43)	1.75 (1.65—1.86)	1.50 (1.41—1.59)	-
	Missing	1.29 (1.15—1.44)	1.42 (1.27—1.58)	1.34 (1.20—1.50)	-
MENTAL HEALTH					
Mental illness	Neither depression nor anxiety	reference	reference	reference	-
	Self-reported depression or anxiety	1.01 (0.97—1.05))	1.09 (1.05—1.13)	1.04 (1.00—1.08))	-
	Missing	1.10 (1.06—1.15)	1.12 (1.08—1.17)	1.12 (1.07—1.16)	-
HEALTH-RELATED BEHAVIORS					
BMI	Underweight	reference	reference	reference	-
	Healthy weight	0.85 (0.76—0.95)	0.79 (0.71—0.88)	0.81 (0.73—0.91)	-
	Overweight	0.79 (0.71—0.88)	0.72 (0.65—0.81)	0.75 (0.67—0.84)	-
	Obese	0.77 (0.69—0.87)	0.74 (0.66—0.82)	0.76 (0.68—0.85)	-
	Missing	0.85 (0.76—0.96)	0.84 (0.75—0.94)	0.85 (0.76—0.96)	-
Non-smoking	No	reference	reference	reference	-
	Yes	0.79 (0.74—0.83)	0.77 (0.73—0.81)	0.76 (0.72—0.81)	-
	Missing	0.86 (0.72—1.03)	0.93 (0.78—1.11))	0.90 (0.76—1.08))	-
Safe alcohol intake	No	reference	reference	reference	-
	Yes	1.06 (1.02—1.10)	1.11 (1.07—1.16)	1.09 (1.05—1.13)	-
	Missing	1.14 (1.04—1.24)	1.33 (1.22—1.45)	1.25 (1.14—1.36)	-
FUNCTIONAL STATUS					
Self-reported health status	Excellent	reference	reference	reference	-
	Very good	1.18 (1.11—1.25)	1.28 (1.21—1.36)	1.24 (1.17—1.32)	-
	Good	1.32 (1.24—1.40)	1.71 (1.61—1.81)	1.57 (1.48—1.66)	-
	Fair	1.61 (1.51—1.73)	2.72 (2.55—2.90)	2.35 (2.20—2.51)	-
	Poor	2.13 (1.94—2.34)	4.76 (4.37—5.19)	3.89 (3.56—4.24)	-
	Missing	1.44 (1.31—1.58)	2.39 (2.20—2.59)	2.09 (1.92—2.27)	-
Health-Related Quality of Life	No limitation	reference	-	-	-
	Minor limitation	0.96 (0.91—1.02)	-	-	-
	Mild limitation	1.10 (1.04—1.16)	-	-	-
	Moderate limitation	1.27 (1.21—1.34)	-	-	-
	Severe limitation	1.66 (1.57—1.75)	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
	Missing	1.31 (1.23—1.39)	-	-	-
Falls History	**0 Falls**	**reference**	-	-	-
	1 Fall	1.07 (1.01—1.12)	-	-	-
	2+ Falls	1.15 (1.10—1.20)	-	-	-
	Missing	1.07 (1.00—1.15)	-	-	-
PRIOR HEALTH SERVICE UTILIZATION					
Previous hospitalization (specify look-back)	**None**	**reference**	-	-	**reference**
	1	0.95 (0.91—1.00)	-	-	0.94 (0.90—0.99)
	2	1.25 (1.16—1.35)	-	-	1.29 (1.20—1.39)
	3+	2.23 (2.03—2.45)	-	-	2.44 (2.22—2.68)
Previous ED use (specify look-back)	**None**	**reference**	-	-	**reference**
	1	1.66 (1.58—1.74)	-	-	1.80 (1.71—1.89)
	2	2.13 (1.96—2.32)	-	-	2.39 (2.20—2.60)
	3	2.18 (1.88—2.53)	-	-	2.54 (2.20—2.94)
	4+	3.24 (2.73—3.84)	-	-	3.79 (3.20—4.48)
Prior acute admission via ED	**Not via ED**	**reference**	-	-	**reference**
	All episode in ED	1.23 (1.11—1.36)	-	-	1.20 (1.08—1.32)
	Admitted via ED	1.28 (1.20—1.37)	-	-	1.26 (1.18—1.35)
	N/S or N/A	0.84 (0.80—0.89)	-	-	0.73 (0.69—0.77)
	No Admission	0.69 (0.66—0.73)	-	-	0.56 (0.53—0.59)
LOS of prior acute admission	**0-2 days**	**reference**	-	-	**reference**
	3-7 days	1.13 (1.06—1.20)	-	-	1.22 (1.15—1.30)
	8-14 days	1.25 (1.14—1.36)	-	-	1.40 (1.28—1.53)
	15-30	1.18 (1.05—1.32)	-	-	1.40 (1.24—1.56)
	over 30 days	1.16 (0.99—1.37)	-	-	1.30 (1.10—1.53)
PRIMARY CARE ACCESSIBILITY					
Prior GP care	**0 visits**	**reference**	-	**reference**	-
	1-3 visits	0.88 (0.82—0.95)	-	0.80 (0.75—0.86)	-
	4-5 visits	0.99 (0.91—1.06)	-	0.94 (0.87—1.01)	-
	6-11 visits	1.17 (1.09—1.25)	-	1.23 (1.15—1.31)	-
	12+ visits	1.60 (1.49—1.72)	-	2.04 (1.91—2.19)	-

† The intercept estimate is the estimated odds of the outcome (hospital readmission within 12 months) when all predictor variables equal their reference values. All other estimates are odds ratios. Estimates in brackets are 95% confidence intervals.

STROBE (Strengthening The Reporting of OBservational Studies in Epidemiology) Checklist

A checklist of items that should be included in reports of observational studies. You must report the page number in your manuscript where you consider each of the items listed in this checklist. If you have not included this information, either revise your manuscript accordingly before submitting or note N/A.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Section and Item	Item No.	Recommendation	Reported on Page No.
Title and Abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2-3
Introduction			
Background/Rationale	2	Explain the scientific background and rationale for the investigation being reported	5-6
Objectives	3	State specific objectives, including any prespecified hypotheses	7
Methods			
Study Design	4	Present key elements of study design early in the paper	7-15
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	7-8
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	N/A
		Case-control study—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls	N/A
		Cross-sectional study—Give the eligibility criteria, and the sources and methods of selection of participants	2, 8
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed	N/A
		Case-control study—For matched studies, give matching criteria and the number of controls per case	N/A
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	10-13

Section and Item	Item No.	Recommendation	Reported on Page No.
Data Sources/ Measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	10-13
Bias	9	Describe any efforts to address potential sources of bias	14
Study Size	10	Explain how the study size was arrived at	8,15
Quantitative Variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	10-13
Statistical Methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	14
		(*b*) Describe any methods used to examine subgroups and interactions	14-15
		(*c*) Explain how missing data were addressed	9
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	N/A N/A N/A
		(*e*) Describe any sensitivity analyses	19
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	15
		(b) Give reasons for non-participation at each stage	15
		(c) Consider use of a flow diagram	N/A
Descriptive Data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Appendix C
		(b) Indicate number of participants with missing data for each variable of interest	Appendix C
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	N/A
Outcome Data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	N/A
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	N/A
		Cross-sectional study—Report numbers of outcome events or summary measures	Appendix C

Section and Item	Item No.	Recommendation	Reported on Page No.
Main Results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	15-19
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other Analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	19
Discussion			
Key Results	18	Summarise key results with reference to study objectives	20-24
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	4, 24
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	20-24
Generalisability	21	Discuss the generalisability (external validity) of the study results	4
Other Information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	25

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

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Predictive Risk Modelling under Different Data Access Scenarios: Who is Identified as High-Risk and for How Long?

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Predictive Risk Modelling under Different Data Access Scenarios: Who is Identified as High-Risk and for How Long?

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ABSTRACT

Objective

This observational study critically explored the performance of different predictive risk models simulating three data access scenarios, comparing: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status over time.

Methods

Cross-sectional health survey data (2006-09) for more than 260,000 Australian adults 45+ years were linked to longitudinal individual hospital, primary care, pharmacy and mortality data. Three risk models predicting acute emergency hospitalisations were explored, simulating conditions where data is accessed through primary care practice management systems, or through hospital based electronic records, or through a hypothetical 'full' model utilizing a wider array of linked data. High-risk patients were identified using different risk-score thresholds. Models were reapplied monthly for 24 months to assess persistence in high-risk categorization.

Results

The three models displayed similar statistical performance. Three-quarters of patients in the high-risk quintile from the 'full' model were also identified using the primary care or

hospital based models, with the remaining patients differing according to age, frailty, multi-morbidity, self-rated health, polypharmacy, prior hospitalisations, and imminent mortality. The use of higher risk prediction thresholds resulted in lower levels of agreement in high-risk designation across models and greater morbidity and mortality in identified patient populations. Persistence of high-risk status varied across approaches according to updated information on utilization history, with up to 25% of patients reassessed as lower-risk within one year.

Conclusion/Implications

Small differences in risk predictors or risk thresholds resulted in comparatively large differences in who was classified as high-risk and for how long. Pragmatic PRM design decisions based on data availability or projected high-risk patient numbers may therefore influence individuals identified as high-risk, overall case-mix, and risk persistence. Routine data linkage would enable greater flexibility in developing and optimizing predictive risk models appropriate to both case-finding and performance measurement applications.

Strengths and Limitations

- This simulation illustrates the extent to which PRMs that rely on different data or modeling specifications will appraise patient risk status differently.
- It also demonstrates how detailed population analyses may augment statistical testing to ensure that PRM algorithms are fit to purpose.
- Linked population and service use data facilitated simulation of several "real world" PRM case-finding and performance measurement applications.
- Simulation findings are intended to be broadly illustrative, not generalizable.
- In practice, case-mix, risk persistence, and high-risk group agreement across alternative PRM applications could differ, due to differences in risk factor availability or measurement, base populations, prediction periods, and other modeling specifications.
- The study population is not representative of NSW, due to oversampling of elderly and rural residents and a low survey response rate (18%) limit.
- Alternatives to conventional logistic regression models (e.g., random effects models or artificial neural networks) were not explored.

INTRODUCTION

To address population health objectives and expenditure growth associated with aging populations and increased chronic disease prevalence, governments and health systems in the UK, Australia, the US and elsewhere are exploring the use of predictive risk modeling (PRM) to better target and integrate services.[1,2,3,4,5] PRM algorithms calculate the probability that a specific patient will experience a future event, such as hospitalisation, based on their unique risk profile. Two different but related applications include identifying individual patients for intervention ("case-finding") and creating high-risk population segments for focused healthcare performance analysis.

Internationally, considerable variability exists in PRM implementations due to differences in health system organization and financing, which affects perceptions of accountability and data access. The entity responsible to administer PRM can be hotly debated, as exemplified by the UK's shift from a centrally-administered algorithm to practice-specific adaptations.[6] PRM requires access to detailed, patient-level risk factor and health service information, ideally, across clinical and community settings and over time. However, for many countries data are non- or partially-linked. Although important to intervention design, limited comparative information exists regarding high-risk patient characteristics identified in different data environments.[7]

A number of review studies compare alternative PRMs with focus on predictive statistics rather than resultant patient profiles and risk persistence.[8,9,10,11,12] Validation studies of

specific instruments also focus on statistical performance, with some also estimating future per-person spending of identified high-risk patients.[13,14,15,16] Billings et al. (2013) is one of the few studies to quantify gains in prediction performance of a hospital-oriented PRM through sequential addition of emergency, outpatient, and general practice information. They also observe that PRMs using non-hospital data identified more lower-acuity patients which could present earlier intervention opportunities.[17] Two studies have found that high-risk population subgroups differ according to the persistence of high-risk status over time.[18,19]

Australia's planned use of PRM in state and national trials provides an opportunity to examine patient profiles under different data access scenarios. For example, the Commonwealth's health care homes initiative will employ an automated PRM using GP data to identify primary care patients who are at-risk of hospitalisation and assess them for allied health service needs and develop multidisciplinary care plans.[20] In parallel, NSW Health will implement an integrated care initiative that will use a hospital algorithm to identify recently discharged patients who need similar supports.[21] Both programs will require that GPs use a standardized care clinical screening tool to determine eligibility for specific services. Despite patient identification efforts that rely on different PRMs using different combinations of GP data, hospital data, and patient survey data, both programs focus on enhanced outpatient care provision to high-risk patients. The likelihood of patient overlap in separately-administered high-risk patient identification efforts is unknown.

This research critically explored the comparative patient identification performance of different PRM algorithms, simulating three common data access scenarios: a 'full' model using all available information, a primary care data only ("GP") model, and a hospital data only ("hospital") model. Using models that draw elements from planned Australian PRMs and patient assessment tools, we assessed: (1) socio-demographic and clinical profiles; (2) consistency in high-risk designation across models; and (3) persistence of high-risk status.

METHODS

Data Sources

The PRMs used population survey and linked health administrative data for participants in the 45 and Up Study. The Sax Institute's 45 and Up Study is drawn from the population of the state of New South Wales (NSW), Australia. Prospective participants were randomly sampled from the Department of Human Services (formerly Medicare Australia) enrolment database, which provides near complete coverage of the population. People 80+ years of age and residents of rural and remote areas were oversampled. A total of 266,942 participants 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. With approximately 18% of those invited responding, participants represent about 11% of the NSW population aged 45 years and older.[22]

This analysis also incorporated information about respondents' health service use and mortality, obtained with patient consent from administrative health databases and linked to their survey responses. This included public and private sector hospital separation and ED presentation information from the NSW admitted patient and emergency department data collections (APDC and EDDC). It also included information about subsidized general practice (GP) care from the Medicare Benefits Schedule (MBS) and prescription drug use form the Pharmaceuticals Benefits Scheme (PBS). Fact of death information was obtained from the NSW Registry of Birth Deaths and Marriages (RBDM).

The Sax Institute used a unique identifier provided from the Australian Department of Human Services to link survey responses to the MBS and PBS that the Department of Human Services (DHS) provided. Using probabilistic methods, the Centre for Health Record Linkage conducted the data linkage of APDC, EDDC and RBDM datasets.

Cohort definition

We created a NSW cross-sectional, population-based cohort (n=263,328) that includes both primary care users as well as those with recent hospitalisations, as these are common target populations in medical home and integrated care initiatives, including those in Australia.

Prediction Outcome and Prediction Period

The PRM algorithms estimated each respondents' probability of experiencing one or more acute emergency admissions during Fiscal Year 09/10. High-risk patients were

identified as those in the highest quintile (top 20%) of predicted probabilities of hospitalisation. Alternative high-risk thresholds – i.e., the top 5% or 10% -- were also examined.

Predictor and descriptive variable definitions

A consolidated list of predictor variables was drawn from tools in use in the Australian integrated care and health care homes trials, which included a validated Canadian PRM that uses hospital data only, a UK PRM that includes GP data, and an Australian-developed clinical assessment tool.[23,24,25,26] (See Appendix A.) Where data limitations prevented matching measure specifications from the three tools, variable definitions drew from previous work associating the predictor with hospitalisation.[27,28,29,30] Covariates included self-reported measures from the 45 and Up Study (including socio-demographics, social support, health status, health behaviors, and functional status) as well as utilization history from the APDC, EDDC and MBS datasets. (See Table 1.) Missing survey responses were included as discrete values under the assumption that programs would likely attempt to estimate risk for patients with missing information, rather than exclude them from consideration for services. Predictor variables were used as PRM covariates and as descriptive variables to characterize the resultant high-risk populations. Additional analysis variables identifying clinical subgroups were created by collapsing or combining PRM predictors.

Table 1: Variables used in predictive risk models

	Model 1 'Full' model	Model 2 Primary care setting	Model 3 Hospital setting	Sensitivity Analysis: Model 2 with GP use
Sociodemographics/Social support				
Age, gender, Aboriginal status, geographic remoteness, SES, marital status	X	X	X	X
Language spoken at home	X	X	-	X
Income, social isolation	X	-	-	
Health status and health behaviours				
Health condition count*	X	X	X	X
Self-rated health*, polypharmacy, anxiety/depression, BMI, smoking status, unsafe alcohol use	X	X	-	X
Functional status, falls	X	-	-	
Prior health service utilisation				
Previous hospitalisations, admission via ED, length of stay of previous hospitalisation, previous ED use	X	-	X	-
Primary care accessibility				
GP use	X	-	-	X
Total number of variables	**23**	**14**	**11**	**15**

Data Note: The survey variables "health condition count" and "self-rated health" were used to approximate the patient health history information that is commonly captured in GP practice management software.

Socio-Demographics and Social Support Predictors

Socio-demographic and social support variables (age, gender, indigenous status, marital status, language, geographic remoteness, socioeconomic status, income, and social isolation) were obtained from the baseline questionnaire. Using birth date, baseline age was updated to reflect respondent age during prediction and subsequent measurement periods. Quintiles of socioeconomic status were derived from residential postcode using the Australian Bureau of Statistics (ABS) Index of Relative Socioeconomic Disadvantage

(SEIFA IRSD).[31] Similarly, the ABS Accessibility Remoteness Index of Australia Plus (ARIA+) was used to classify remoteness into major city, inner regional, outer regional, remote and very remote categories.[32] Indigenous status (yes/no) included those who self-identified as Aboriginal or Torres Strait Islander, or both. Income was based on *"usual yearly household income before tax, from all sources"* and categorized into $10K increments through $70K. Social isolation was identified as a response of "no one" to a survey question that asked, *"how many people outside your home, but within one hour of travel, do you feel you can depend on or feel very close to?"*

Health Status and Health Behaviours Predictors

To ensure consistency in covariate measurement across the three PRM models, all health status and health behavior measures were calculated from the baseline survey even when also available in administrative data. Several predictors consisted of risk factor counts. The health condition count summed self-reported chronic conditions (0, 1, 2, 3+) according to participants' responses to the questions "*Has a doctor ever told you that you have ...*?" or "*In the last month have you been treated for ...?"* The eight conditions counted were: heart disease, diabetes, high blood pressure, stroke, blood clots, cancer, asthma, or Parkinson's disease. The depression/anxiety measure (yes/no) was also derived from these same questions. The polypharmacy variable totaled the number of medications (0, 1-4, 5+) that respondents had "*taken most of the last 4 weeks*", as selected from a list of common medications. The falls count (0,1,2+) was based on the question, "*during the past 12 months, how many times have you fallen to the floor or the ground?*"

Additional predictors were derived from validated items or short standardised scales included in the 45 and Up baseline questionnaire. Self-rated health (SF-1) was reported as excellent, very good, good, fair or poor. The Body Mass Index (BMI) was collected in Kg/M^2 and responses were classified as underweight (<18.5), normal weight (18.6-25), overweight (26–30), and obese (>30). The question "*are you a regular smoker now?*" was used to assess baseline smoking status. Alcohol use was estimated from self-reports of *"about how many alcoholic drinks do you have each week?"* with unsafe use defined as more than 14 per week (adjusted for 9% under-reporting).[33] Functional capacity was defined according to the Medical Outcomes Study, Short Form 36 Physical Functioning Scale scores, with no limitation corresponding to a score of (100), minor limitation (95–99), mild (85-94), moderate (60–84) and severe limitation (0–59).[34]

Prior Hospital/ED Utilization and Primary Care Accessibility

APDC, EDDC and MBS administrative datasets were used to calculate prior utilization predictors. Variable specifications for the hospitalisation-related covariates were based on the Ontario HARP. Utilization predictors included: acute admission six months prior (0,1,2,3+), length of stay of prior acute admission (0-2, 3-7, 8-14, 15-30, 31+), admission via emergency department (yes/no), emergency department visits six months prior (0,1,2,3,4+). GP visits in the prior twelve months were also calculated and classified as (0, 1-3,4-5, 6-11, 12+).[35] Look-back periods for prior hospital, ED, and GP service use were calculated from the start of the prediction period (July 1, 2009.)

Population Subgroups

Frail elderly were defined as individuals 65+years that reported severe physical limitations and/or 2 or more falls in the last year.[36] Super-utilizers were those with 2+ acute admissions in the previous 6 months. Fair/poor health indicates those whose self-rated health was fair or poor and multi-morbid individuals were those with 2+ health conditions. Those who died during the prediction year are classified as end-of-life. Although these subpopulations were selected because they are often considered clinically distinctive, they are not mutually exclusive designations.

PRM Modeling Scenarios

Three PRM models were developed to simulate high-risk population identification within alternative data environments. These simulations used a combination of service use and population survey data to approximate data commonly captured through hospital EHRs, GP practice management systems, and clinical assessment tools.

PRM-1 ("full model") was built with comprehensive, linked data and used the full, consolidated list of predictor variables to define high-risk status. In addition to data elements routinely available in GP and hospital settings, it included less-commonly collected risk factors such as income, social isolation, and functional status. PRM-2 ("GP model") simulates a primary care-based implementation. Based on the capabilities of the

most common practice management software in Australia, GPs were assumed to have electronic access to socio-demographics, language, health/mental health status, and health behaviours. Conversely, the GP model did not include prior hospitalisation, ED or GP visit information because common GP practice management software does not track utilization history. While practices often have separate business software that includes GP visits, only very sophisticated practices have the data skills to link business information and clinical information for analysis. We did, however, conduct sensitivity analyses on our decision to exclude past GP use via a GP+ model that included GP utilisation. Finally, PRM-3 ("hospital model") assumed that primary care patient rosters were matched with hospital administrative data, providing access to patient demographics, health status, as well as past hospital and ED use. This data matching assumption reflected actual practice in Australia's integrated care pilot and ensured consistency in the base population across the three PRM test scenarios. (See Table 1 for model-specific risk predictors).

All models used a logistic regression to predict the outcome of any acute emergency hospitalisation in Fiscal Year 09/10. The extent to which high-risk individuals were admitted to hospital as predicted (positive predictive value) was assessed and the c-statistic was calculated.[37] All statistical analyses were performed in SAS version 9.4 (SAS Institute Inc., Cary, NC, USA).

Descriptive Analysis and Assessment of Persistence

We compared case-mix, identification consistency, and risk persistence among the high-risk populations identified by each model. High-risk persistence refers to the proportion of high-risk individuals that continue to be (or re-achieve) high-risk status. To assess the persistence, we identified individuals in the high-risk quintiles for four models. Two GP models were included in this analysis, with and without GP utilization history as a predictor variable. We recalculated the risk quintile of these high-risk people on a monthly basis over a two-year period, applying updated age and utilization risk factor information. All other risk predictors were measured at solely baseline, so are not time-varying covariates. Individuals who died during the prediction period were removed from this analysis in the month of their death.

Ethics

The 45 and Up Study was approved by the University of New South Wales Human Research Ethics Committee (HREC). Additionally, this research, inclusive of data linkage, was approved by the NSW Population and Health Services Research Ethics Committee (HREC/15/CIPHS/42, 04/10/16).

RESULTS

Of the 266,942 participants in the 45 and Up Study, n=266,519 were eligible for inclusion because they used a hospital/ED/medical/pharmacy service between July 2006-

June 2009. Of these, n=3182 were excluded as they died prior to the 1-year prediction period (June 30, 2009). An additional n=9 were excluded for possible linkage errors, leaving 263,328 patients for analysis. Characteristics of the full population is provided in Appendix B.

The probability threshold for the high-risk quintiles were low for all models (12.0 - 13.1%). Approximately one-quarter (22.2-24.9%) of patients in the top risk quintile experienced an emergency admission during the prediction year (positive predictive value) and these high-risk patient admissions represent one-half (48.9-54.8%) of total admissions (sensitivity). Statistical performance of the three PRM scenarios was very similar, with moderately strong c-statistics for all models, ranging .74 to .77.

Despite similarities in predictive accuracy, the three PRM scenarios yielded different high-risk individuals and population characteristics (Figure 1).

Sharing three-quarters (74%) of patients in common with the full model, the primary care model high risk group includes more multi-morbid individuals (62.8% vs. 55.9%) and those in fair/poor health (43.2% vs. 39.5%) but fewer super-utilizers (8.0% vs. 13.4%) and those at the end-of-life (3.9% vs. 4.4%). The hospital high-risk quintile also agreed with the full model one three quarters of the time (77%). Across the three models, the hospital high-risk group includes the lowest proportion of frail elderly (34.4% vs. 42.3%) and those in fair/poor health (27.5% vs. 43.2%) and highest proportion of super-utilizers

(14.3% vs. 8.0%). These case mix differences across high-risk quintiles are driven by differences among the one-quarter of patients not shared in common. (See Figure 2.)

Nearly two-thirds (59%) of the top quintile of high-risk individuals were consistently identified within all three models (see Figure 2). As compared to the full model, this overlap group has higher morbidity and mortality: with multi-morbid individuals (69.6% vs. 55.9%), frail elderly (50.1% vs. 42.3%) in fair/poor health (42.7% vs. 39.5%) and very old (31.4% vs. 18.7%). They are also somewhat more likely to be at the end of life (5.7% vs. 4.4%). As the high-risk threshold is increased to the 90th or 95th decile, positive predictive values increase in the range of 28.3-33.5 and 34.3-41.8 respectively, but the models' intersection decreases, falling to 48% and 39% shared patients, respectively. This results primarily from the GP model diverging from the other two. (Appendix B.)

Table 2 summarizes the extent to which characteristics of the high-risk patient cohort changed when using different models or risk prediction thresholds. High-risk group acuity increased dramatically as high-risk thresholds increased. Proportions of very old, frail elderly, multi-morbid individuals, super-utilizers and those who report fair/poor health increased by more than 10 percentage points. With the exception of age and marital status, there was little change (<5 percentage points) in the sociodemographic and behavioral profile of high-risk patients, irrespective of model or high-risk threshold. Although not all population characteristics were explicitly measured in all models (See Figure 1), this did not consistently affect their prevalence in high-risk groups. For example, functional status was measured explicitly only in the full model, but individuals

with severe functional limitations accounted for at least one-third of high-risk quintile patients (32.3-45.5%) across models. In general, patient characteristics with high odds ratios (>1.3) were the most sensitive to modeling specifications. (See Appendix C for odds ratios and Appendix B for selected case-mix characteristics by model and threshold.)

Table 2: Variability in case mix among patients identified as 'high risk' when varying modelling approach or high risk admission thresholds

	Case Mix Changes: Average percentage point spread between minimum and maximum population proportions					
	Same Threshold, Different models "Model Effect"			Same Model, Different Thresholds "Threshold Effect"		
	<5	5-10	>10	<5	5-10	>10
Frail Elderly			X			X
Super-Utilizers (Hospital, ED, GP)			X			X
Individuals reporting Fair/Poor Health			X			X
Very Old (85+ years)		X				X
People taking 5+ Medications			X		X	
Individuals reporting Excellent/Very Good Health			X		X	
Multi-Morbid Individuals		X			X	
Middle-Aged Adults (45-64 years)		X			X	
People at End-of-Life	X			X		
Unmarried Persons	X				X	
Persons with Depression/Anxiety	X			X		
Socio-demographic Groups (Males, Low-Income, Residents of Most Disadvantaged Areas, Rural Residents Non-English Speakers)	X			X		

Figure 3 illustrates that four in five (78.8%) high-risk individuals for the full model and three of four (74.3%) in the hospital model remain persistently high-risk when re-evaluated over a two-year period. For these models, approximately 20-25% of high-risk group members gradually lose high-risk status throughout the first year following identification. High-risk group membership stabilizes thereafter.

Reduction in risk status results from individuals no longer meeting the "prior ED" or "prior hospitalisation" criteria, which are used to assess risk in the full and hospital models. By contrast, all of the GP high-risk quintile (100%) remained persistently high risk, because only age changed over the two-year period. Unlike the other two models, the GP model did not include prior utilization history, and all other risk factors were measured solely at baseline. While advancing age increases risk status, this analysis focuses on individuals already at highest risk. As a result, for a fixed survey cohort, high-risk status did not vary over time. In the GP+ model that included GP usage history, 12.9% of high-risk individuals identified with the GP+ model lost high-risk status over two years.

DISCUSSION

To effectively leverage PRM as part of the implementation of medical home, integrated care and other quality improvement efforts, stakeholders need to know whether they are targeting the "right" patients and to understand how well health systems are currently performing for them. Who is the "right" patient depends on the clinical or measurement

context. Our study demonstrated sensitivity of case-mix and risk persistence to PRM specifications, resulting in somewhat different target populations with different hospitalisation risks. One cannot rely solely on predictive performance to assess model suitability for either clinical or evaluative purposes.

Among our population-based cohort, all three models resulted in high-risk quintiles that included relatively low cut-points for the risk of admission (12-13%), with one-in-four individuals subsequently hospitalized. The large number of people with lower risk scores meant that the high-risk population was sensitive to varying risk predictors and thresholds. As high-risk thresholds increased, case-mix was increasingly characterized by high proportions of very old, frail elderly, multi-morbid individuals, and those who report fair/poor health. At the 95th percentile, for example, more than one in four high-risk group members had a history of repeat hospitalisations and nearly one in 10 would die during the prediction year. Differences between high-risk groups reflected the strongest PRM predictors, highlighting the need to ensure the modeling specifications are optimized to "find cases" appropriate for the intervention.

Risk status may be conceptualized as something that changes over time (e.g., as an outcome) or it may be thought of as a relatively stable characteristic of a patient or a population. How long a person remained high-risk depended on the PRM's relative reliance on factors that could change over time – only age and recent utilization history in our models. Risk status was least stable in PRMs that incorporated prior hospital use. It is common in clinical settings to have access to both time-variant and -invariant patient

data. Some patient information is regularly updated (e.g., utilization history, age). Other patient data does not typically change (gender, race/ethnicity). Still other information maybe collected once for a specific purpose or infrequently reassessed (e.g., eligibility screening data).

Case Finding Implications

Case-finding PRM applications seek to target interventions by identifying patients at-risk of hospitalisation. Our results demonstrate that fully or partially-linked data identified high-risk patients who would not have been classified as such using GP data alone - for example, super-utilizers with multiple prior hospitalisations. In a general practice setting, such patients may not have been targeted for closer monitoring, especially if they were out-of-care or new to the practice. Sharing actionable information across data settings is a clear value-add and often an explicit motivation for predictive risk modeling.

Whether a patient's high-risk status is relatively more persistent or episodic also has bearing on case-finding. For example, if risk manifests episodically, clinical interventions may be short-term and time-sensitive. To identify new at-risk patients in near real-time, the PRM base population may need to be updated and reassessed more frequently. In practice, not all variables commonly used in PRMs are available on a real-time basis, including those (e.g., hospitalisation history) that influence risk persistence.[38] If data lags

are long, the window of opportunity for intervention may close before providers become aware of a change in risk status.

Performance Measurement Implications

Additional considerations apply for the use of PRM in performance measurement applications. Here, the aim is to define high-risk population segments, for example, to understand how well health systems have been performing for high-risk populations and evaluate the impact of new models of care. PRM-defined population segments could be used to describe the regional distribution of high-risk populations and to assess past and current service use, morbidity, mortality, and other medical home/integrated care outcomes. Fair and appropriate performance measurement therefore requires a reasonable match between target populations identified via case-finding and corresponding performance measurement populations. Yet in our findings, only three-quarters of patients, at best, were commonly identified using data available in different settings. While the minimum degree of agreement necessary for analysis may differ across performance measurement applications – e.g., program evaluation may differ from on-going health system reporting -- it is clear that clinical intervention and performance populations will not be fully equivalent unless they are using exactly the same data.

Even with identical data, pragmatic data analysis decisions could inadvertently introduce bias. For example, case-finding applications often set risk thresholds high due to clinical capacity constraints,[39] while performance measurement applications may prefer larger

risk groups to ensure adequate sample size for analysis. In our simulation, morbidity and mortality dramatically increased as risk thresholds increased. Therefore, creating a larger analysis population by relaxing the PRM high-risk threshold would not only increase sample size (intended), it would also change case-mix (unintended).

Stratified approaches to performance measurement also need to reflect on the persistence of high-risk status relative to the outcome assessment timeframe. Stratified analysis is well-suited for short-term outcomes that are measured soon after patients are classified as high-risk, such as care planning or readmission. However, medical home and integrated care initiatives often aim to reduce long-term hospitalisation rates and costs, measured years later.[40] In our simulation, up to 20% of high-risk patients in the full model and 25% identified via the hospital model would change risk status within a year of identification. From a performance measurement perspective, this means that high-risk patients that become lower risk over time – whether due to usual care or program interventions -- would no longer be counted among the "high-risk" strata for which outcomes are reported, unless methodological steps were employed to retain them.

Theoretically, variation in care could also be reflected in risk status, and persistence of high-risk status could potentially be explored as an outcome of care to be assessed as part of performance measurement. The GP model, with regularly updated risk factor information related to health behaviours and self-rated health, might work well for this purpose. By contrast, the hospital model is highly endogenous, with recent hospitalisation history a key determinant in establishing current (hospitalisation) risk

status. Because risk scores in this instance track with recent hospital use, monitoring hospitalisation patterns may provide a more direct means for benchmarking and evaluating variation in care. Given the predominantly time-invariant variables in our study, we did not attempt to investigate the utility of risk status persistence as an outcome but highlight it as a promising area for future research.

Regional differences may emerge in stratified performance outcomes or in high-risk patients' rates of return to lower risk status. Designing meaningful comparisons of performance across sites will require careful consideration. Within the broader high-risk population segment, case mix is likely to differ by clinical site, especially if they implement PRMs tailored to their populations. Even with a standard PRM, known regional variations in demographics and health status will likely result in some sites having high-risk groups dominated by frail elderly, others by super-utilizers, and still others by the multi-morbid. For certain performance comparisons, it may be necessary to risk-adjust (within risk strata) or further stratify (e.g., by subgroup) to account for this heterogeneity. This area is also ripe for additional research.

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Competing Interests

All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare grants from the Commonwealth Department of Health (TLJ, LJ, MOF) and Centre for Health Economics Research and Evaluation (TLJ), infrastructure support from the Bureau of Health Information (TLJ, JFL, KS, JH) and NSW Ministry of Health (JH), and LJ is a member of the governing board of the Bureau of Health information; research results may inform evaluation/performance measurement for the Department of Health and Bureau of Health Information.

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Contributors

TLJ conceived the study, undertook the literature review, implemented the regression models, conducted descriptive analyses and wrote the first draft. JK provided important intellectual contributions to study design and led the statistical and descriptive analyses. MOF produced some of the regression predictors, contributed substantively to the analysis and intellectual content, and provided detailed revisions throughout the article drafting process. JH conducted analyses and critically reviewed the methodology sections of the paper. KS, LJ and JFL served as project mentors, providing significant ideas to the development of the model and important intellectual content throughout the draft revision process. All authors have read and approved the final version of the manuscript.

Transparency declaration

I, Tracy L. Johnson (corresponding author), affirm that the manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned have been explained.

Data Sharing

The patient level data from 45andUp Survey are available to researchers according to its governance framework. See https://www.saxinstitute.org.au/our-work/45-up-study/for-researchers/ for further details.

Copyright

Figure 1: Comparison of High-Risk Quintiles from the Full, GP and Hospital scenarios

Figure 2: Intersection of Models for Different High Risk Thresholds

Figure 3: Persistence of High-Risk Group Status over Time:
% of Original HR Quintile that are High Risk in Subsequent 24 Months

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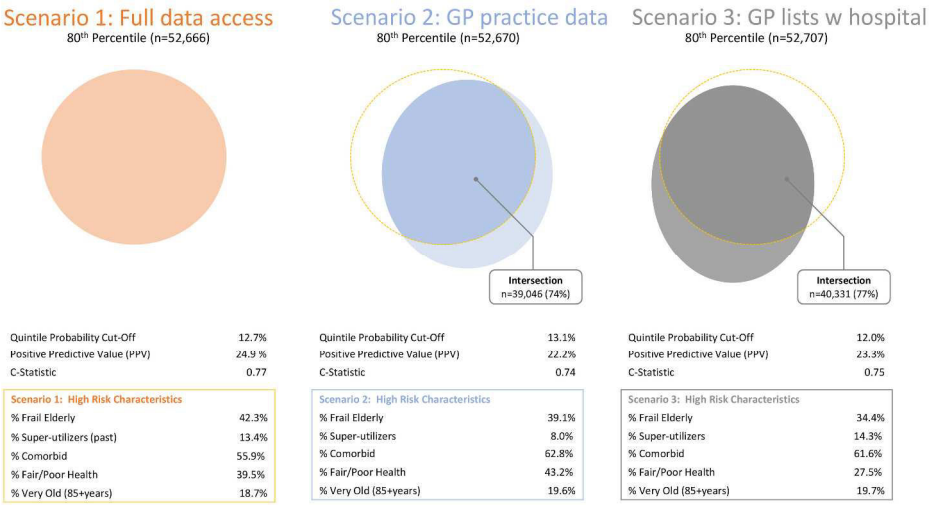

Figure 1: Comparison of High-Risk Quintiles from the Full, GP and Hospital scenarios

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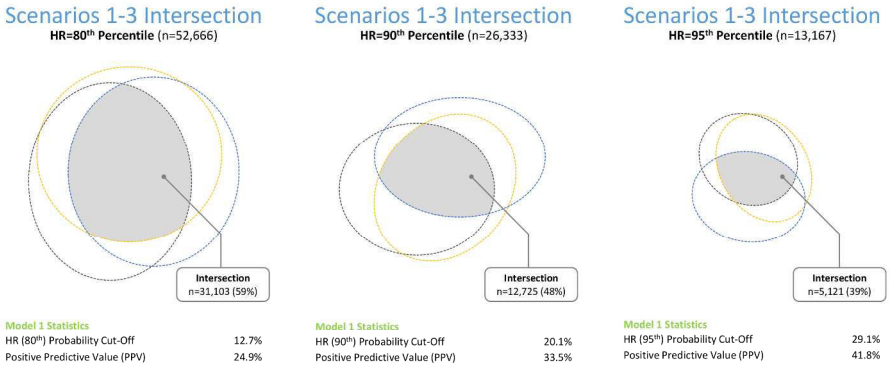

Figure 2: Intersection of Models for Different High Risk Thresholds

273x127mm (300 x 300 DPI)

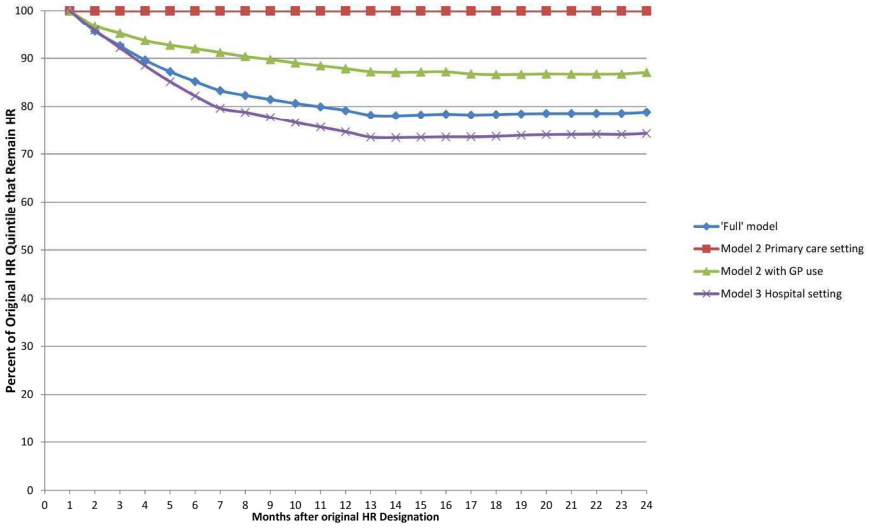

Figure 3: Persistence of High-Risk Group Status over Time:
% of Original HR Quintile that are High Risk in Subsequent 24 Months

199x130mm (300 x 300 DPI)

Appendix A: Comparison of predictive risk models under consideration in Australia

PRM Features	NSW Stage 1: Ontario-HARP[i] (complex)	Commonwealth Stage 1: Qadmissions[ii]	Commonwealth Stage 2: Chronic Condition Risk Calculator: "Victoria HARP"	Consolidated List of Available Predictor Variables
Design Elements				
Required data sources	**Hospital EHR**	**GP practice management & hospital EHR**	**GP practice management & assessment data**	**APDC, EDDC, MBS, 45andUp survey, mortality**
Unit of Analysis	**discharge**	**person**	**person**	**Person**
Cohort definition	acute discharges	primary care population	primary care population (for Commonwealth application)	45and Up Survey respondents (with a MBS, EDDC, or APDC linked record)
Prediction Period	**15 mos post-index discharge**	**2 years post index time**	**12 mos post assessment**	**12 mos post index time**
Prediction Outcome	acute presentation (readmission)	1+ emergency admissions	acute presentation	1+ acute, emergency admits
Covariates Used				
Number and types covariates in final model	9 (complex model)	14	21	26 (to test)
SOCIODEMOGRAPHICS				
Age	✓	✓	x	✓
Gender	x	✓	x	✓
Income/Income Decile	x	x	✓	✓
Index of relative SES disadvantage	x	✓	x	✓
Remoteness/Rurality	x	✓ (n=10 regions)	x	✓
Ancestry/Race/Ethnicity	x	✓	x	✓
Aboriginal/Torres Strait Islander	x	x	✓	✓
Language other than English	x	x	✓	✓
Transportation	x	x	✓	X
Housing stability	x	x	✓	X
Asthma triggers	x	x	✓	X
SOCIAL SUPPORT				
Marital status	x	x	x	✓
Caregiver / Other Social Support	x	x	✓	✓
HEALTH STATUS				
Comorbidity Score/Count	✓	x	x	✓
Specific conditions (DX)	✓ (n=19)	✓ (n=12)	✓ (n=7)	✓ (tested, not used)
Illness Severity/Resources Intensity	✓	x	x	x
Specific medications/ polypharmacy/regimen changes	x	✓ (n=5)	✓ (n=2)	✓
Clinical indicators (lab values, PX, etc.)	x	✓ (n=3)	✓	x
Mental illness	x	✓	✓	✓
Drug use/abuse	x	x	✓	x
HEALTH-RELATED BEHAVIORS				
BMI	x	✓	✓	✓
Smoking status	x	✓	✓	✓
Alcohol use	x	✓	✓	✓
Physical Activity	x	x	✓	✓ (tested, not used)
Readiness to Change	x	x	✓ (n=7)	x
FUNCTIONAL STATUS				
Self-reported health status	x	x	x	✓
Health-Related Quality of Life (functional status, disability, self-care)	x	x	✓	✓
Other measures of functional status (mobility, fall history, pain, cognitive impairment, frailty)	x	✓ (falls)	✓ (dementia, pain,falls, incontinence)	✓ (falls)

PRIOR HOSPITAL/ED UTILIZATION				
Index Admit LOS	✓	x	x	✓
Discharge disposition	✓	x	x	x
Previous hospitalizations	✓	✓	✓	✓
Admit via ED	✓	x	x	✓
Previous ED use	✓	x	x	✓
ACCESSIBILITY				
GP care	X	x	✓	✓

[i] Canadian Institute for Health Information. Early Identification of People At-Risk of Hospitalization: Hospital Admission Risk Prediction (HARP) – a new tool for supporting providers and patients. Technical Appendix. Queen's Printer for Ontario: 2013. https://secure.cihi.ca/free_products/HARP_reportv_En.pdf (retrieved 05/03/17)

[ii] Hippisley-Cox J, Coupland C. Predicting risk of emergency admission to hospital using primary care data: derivation and validation of QAdmissions score. *BMJ Open*. 2013;3:e003482.

Population Characteristics by Model and High-Risk Threshhold

Characteristic	Full sample	80% threshold			90% threshold			95% threshold			Model 1-3 intersection		
		Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	Model 1: Full data access	Model 2: Primary care data	Model 3: Hospital data	80% threshold	90% threshold	95% threshold
SUMMARY STATISTICS													
n (Sample size)	263,328												
n (HR group size)		52,666	52,670	52,707	26,333	26,333	26,372	13,167	13,173	13,189	31,103	12,725	5,121
% (Model agreement)											59	48	39
n (Patients readmitted to hospital)	23,966	13,132	11,712	12,306	8,834	7,451	8,153	5,503	4,508	5,205	8,991	4,851	2,453
HR group probability cut-off		12.7	13.1	12.0	20.1	19.1	18.2	29.1	25.9	26.8			
Positive predictive value (PPV)		24.9	22.2	23.3	33.5	28.3	30.9	41.8	34.2	39.5	28.9	38.1	47.9
Sensitivity		54.8	48.9	51.3	36.9	31.1	34.0	23.0	18.8	21.7	37.5	20.2	10.2
C-statistic (overall)		0.77	0.74	0.75	0.77	0.74	0.75	0.77	0.74	0.75			
SPECIAL POPULATIONS													
Frail elderly [1]	11.2	42.3	39.1	34.4	54.1	52.5	42.1	61.6	62.9	49.1	50.1	63.5	72.5
Multi-morbid (2+ conditions)	23.8	55.9	62.8	61.6	61.7	69.3	62.7	65.0	73.4	68.6	69.6	72.1	78.3
Fair/poor self-reported health	13.3	39.5	43.2	27.5	48.1	58.0	32.5	53.7	65.9	37.6	42.7	54.4	64.1
Super-utilizers[2]	3.6	13.4	8.0	14.3	20.6	9.6	22.3	30.1	11.1	31.9	13.1	18.7	25.3
Died in prediction year	1.1	4.4	3.9	4.2	6.9	5.6	6.4	9.9	7.6	9.3	5.7	8.8	12.7
SELECT RISK FACTORS													
Age (years)													
45-64	58.3	16.4	10.9	12.0	12.7	7.0	9.7	10.6	4.3	7.1	5.2	3.5	2.3
65-84	37.7	64.8	69.5	68.2	58.7	58.3	58.6	53.7	45.4	54.2	63.4	44.8	34.1
85+ years	4.0	18.7	19.6	19.7	28.6	34.7	31.7	35.7	50.3	38.7	31.4	51.7	63.5
Male	46.1	54.8	57.1	56.3	55.5	56.9	56.4	56.4	55.9	56.3	57.0	56.2	56.5
Annual income <$30,000	29.0	53.2	53.1	50.3	54.7	55.9	52.6	55.1	56.5	53.7	55.5	56.3	56.7

Remoteness: outer/remote/ very remote	11.2	13.3	13.8	14.0	13.2	13.5	13.5	12.5	13.1	12.2	13.7	13.2	12.6
Most disadvantaged (IRSD)	20.8	31.9	33.6	32.9	33.3	35.7	34.3	34.0	36.7	35.7	34.9	36.9	38.4
Non-English speaker	9.5	9.8	9.7	8.9	9.8	10.1	9.5	9.8	10.7	9.6	9.5	10.0	10.6
Indigenous													
Not married	30.5	44.0	45.7	44.2	47.9	50.8	49.4	50.4	56.1	52.3	49.2	55.7	60.0
Socially isolated	6.3	6.9	7.4	6.4	7.0	7.7	6.6	7.2	7.8	6.4	6.7	6.9	7.3
# chronic conditions													
0	41.1	14.4	11.0	12.4	12.0	8.5	10.4	10.3	7.3	9.3	9.2	6.6	5.2
1	35.1	29.7	26.2	26.0	26.2	22.2	26.9	24.6	19.2	22.1	21.2	21.3	16.5
Heart disease	11.7	30.3	33.3	32.0	35.5	39.7	35.0	38.9	44.5	39.3	38.8	43.7	49.1
High blood pressure	35.5	55.9	61.2	59.9	57.3	63.0	59.5	58.1	64.3	61.5	63.1	62.5	64.8
Cancer (excluding skin cancers)	15.6	27.9	29.6	32.3	29.8	32.1	33.1	31.4	33.8	35.1	34.0	35.2	38.1
Stroke	3.1	9.9	10.5	10.1	12.7	13.9	11.8	14.7	16.7	14.6	13.4	16.4	20.3
Diabetes	8.9	20.6	23.7	21.5	23.2	27.5	22.2	24.1	29.4	24.0	25.5	26.7	28.6
Blood clot	4.6	10.5	10.8	11.0	12.0	12.6	11.8	13.4	14.0	13.6	12.9	14.2	16.4
Asthma	12.6	18.0	18.9	18.9	19.3	20.6	18.8	20.5	22.1	20.1	20.2	21.1	23.6
Parkinson's disease	0.6	1.8	1.9	1.8	2.3	2.6	2.0	2.8	3.0	2.5	2.3	2.9	3.5
# medications													
0	35.8	10.5	7.7	13.8	8.7	6.0	12.4	7.8	4.8	11.1	7.5	6.0	4.4
1-4	57.6	69.6	70.1	69.6	66.4	63.7	68.7	64.1	59.4	67.5	67.9	64.1	60.7
5+	5.1	18.1	20.5	15.3	23.1	28.5	17.4	26.3	34.1	19.9	22.9	28.0	33.2
Missing	1.5	1.7	1.8	1.4	1.8	1.8	1.5	1.8	1.7	1.5	1.7	1.9	1.7
Depression or Anxiety	16.3	19.5	19.6	16.0	20.2	20.7	16.3	20.4	21.3	16.2	17.7	18.3	19.1
Body mass index													
Underweight	1.2	2.3	2.4	1.8	2.9	3.1	2.1	3.3	3.9	2.3	2.5	3.2	3.8
Obese	20.7	23.7	23.9	22.2	22.5	22.9	20.6	21.3	20.8	19.9	22.4	19.3	17.8
Smoker	7.1	8.7	8.9	5.3	8.4	8.5	5.2	8.1	7.9	5.0	6.1	5.4	5.5

Unsafe alcohol intake	18.4	15.1	14.8	17.1	13.7	12.5	15.2	12.6	10.6	14.1	14.2	11.7	9.9
Self-reported health													
Excellent/very good	50.6	16.6	10.9	28.5	12.3	7.4	23.9	10.1	4.5	20.1	12.2	8.5	4.9
Good	32.6	37.3	38.3	39.2	32.6	27.1	38.1	29.3	21.8	36.4	38.4	29.5	23.2
Missing	3.5	6.6	7.7	4.8	6.9	7.5	5.5	7.0	7.8	5.9	6.8	7.5	7.8
Severe functional limitation	13.4	45.5	39.3	32.3	56.3	51.5	39.6	63.1	60.6	45.8	46.8	59.6	68.7
2+ falls in last 12 months	9.3	21.1	18.3	16.1	25.7	22.4	19.1	29.6	26.3	21.9	21.2	25.9	30.1
# hospitalisations in last 6 months													
0	84.8	62.3	74.1	59.4	50.6	70.9	46.6	37.3	68.3	33.7	62.0	52.5	42.2
1	11.7	24.3	18.0	26.3	28.8	19.5	31.0	32.6	20.5	34.4	24.9	28.8	32.5
# ED visits in last 6 months													
None	91.8	73.1	84.4	71.2	59.7	81.3	56.2	43.3	78.2	39.6	74.3	63.3	49.3
4+	0.3	1.4	0.8	1.4	2.6	1.1	2.7	4.7	1.5	4.9	1.4	2.2	3.9
Admitted to hospital via ED[3]	4.2	17.4	10.9	18.7	28.0	14.3	30.8	41.3	17.9	44.5	18.4	28.9	43.1
1-2 days length of stay[4]	20.4	37.7	28.3	41.4	40.5	28.9	44.2	41.0	28.9	41.5	38.2	39.7	38.3
# previous GP visits in last 6 months													
0	6.5	4.1	4.9	4.6	4.8	6.6	5.9	5.1	8.4	7.1	5.8	8.0	8.9
12+	16.6	52.7	39.1	39.9	62.6	44.8	47.5	69.4	47.9	53.5	49.7	56.6	61.3

[1] Age 65+ years with either severe functional limitations or at least two falls
[2] At least two hospital admissions in last 6 months
[3] Hospitalisations in last 6 months
[4] Last hospitalisation

Appendix C: Odds ratio estimates for 12-mos hospital readmission predictive risk models†

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
Data Access Assumptions		Hospital, GP practice management and GP use data, Assessment data (functional status, social support, income)	GP patient management data (patient history only, no use data)	GP patient management data (patient history & use data)	Hospital administrative data & GP patient lists (demographics, not practice management data)
Model intercept†		0.06 (0.05—0.07)	0.04 (0.04—0.05)	0.04 (0.04—0.05)	0.07 (0.07—0.08)
DEMOGRAPHICS/SOCIAL DETERMINANTS OF HEALTH					
Age	45-64	reference	reference	reference	reference
	65-84	1.58 (1.53—1.64)	2.09 (2.03—2.16)	1.82 (1.76—1.88)	1.94 (1.88—2.01)
	85+	3.32 (3.13—3.52)	5.37 (5.10—5.66)	4.56 (4.33—4.81)	4.95 (4.70—5.22)
Gender	Male	reference	reference	reference	reference
	Female	0.74 (0.72—0.76)	0.78 (0.76—0.80)	0.76 (0.74—0.78)	0.83 (0.81—0.86)
Annual Household Income	<10,000	reference	-	-	-
	10,000-29,999	0.94 (0.89—0.99)	-	-	-
	30,000-49,999	0.89 (0.83—0.94)	-	-	-
	50,000-69,999	0.82 (0.77—0.89)	-	-	-
	70,000 or more	0.79 (0.73—0.84)	-	-	-
	Do not wish to answer	0.94 (0.89—1.00)	-	-	-
	Missing	1.08 (1.01—1.17)	-	-	-
Accessibility/ Remoteness Index of Australia (ARIA+)	Metropolitan	reference	reference	reference	reference
	Inner regional	1.09 (1.05—1.12)	1.04 (1.00—1.07)	1.11 (1.08—1.15)	1.00 (0.96—1.03)
	Outer/remote /v.remote	1.26 (1.20—1.32)	1.18 (1.12—1.23)	1.27 (1.21—1.33)	1.16 (1.11—1.22)
	Missing	1.33 (1.19—1.49)	1.28 (1.15—1.43)	1.37 (1.22—1.53)	1.21 (1.08—1.35)
Index Relative Socioeconomic Disadvantage (ISRD)	Quintile 1 (Most Disadvantaged)	reference	reference	reference	reference
	Quintile 2	0.95 (0.91—0.99)	0.91 (0.88—0.95)	0.93 (0.89—0.97)	0.89 (0.85—0.92)
	Quintile 3	0.96 (0.92—1.00)	0.89 (0.85—0.93)	0.92 (0.88—0.96)	0.85 (0.81—0.89)
	Quintile 4	0.94 (0.89—0.98)	0.84 (0.80—0.88)	0.88 (0.84—0.93)	0.79 (0.75—0.83)
	Quintile 5 (Least Disadvantaged)	0.94 (0.89—0.98)	0.80 (0.76—0.84)	0.86 (0.82—0.90)	0.72 (0.69—0.76)
	Missing	0.12 (0.07—0.22)	0.08 (0.05—0.15)	0.10 (0.05—0.17)	0.09 (0.05—0.17)
Aboriginal/Torres Strait Islander	No	reference	reference	reference	reference
	Aboriginal or TSI	not published	not published	not published	not published
	Missing	not published	not published	not published	not published
Language other than English	No	reference	reference	reference	-
	Yes	0.89 (0.84—0.93)	0.93 (0.88—0.97)	0.88 (0.83—0.92)	-
SOCIAL SUPPORT					
Married at Baseline	No	reference	reference	reference	reference
	Yes	1.13 (1.10—1.17)	1.21 (1.17—1.24)	1.20 (1.16—1.24)	1.23 (1.19—1.27)
People to Depend on	No one to depend on	reference	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
(Social Support)	1+ people to depend on	1.05 (0.99—1.12)	-	-	-
	Missing	1.15 (1.06—1.25)	-	-	-
HEALTH CONDITIONS					
Comorbidity Score/Count	No Chronic conditions	reference	reference	reference	reference
	1 Chronic condition	1.14 (1.09—1.18)	1.19 (1.15—1.24)	1.15 (1.11—1.19)	1.30 (1.25—1.34)
	2 Chronic conditions	1.33 (1.27—1.39)	1.50 (1.43—1.56)	1.38 (1.32—1.44)	1.78 (1.71—1.85)
	3+ Chronic conditions	1.53 (1.45—1.61)	1.88 (1.78—1.97)	1.68 (1.59—1.77)	2.48 (2.37—2.61)
Polypharmacy	0 Medications	reference	reference	reference	-
	1-4 Medications	1.14 (1.10—1.19)	1.28 (1.23—1.33)	1.18 (1.14—1.22)	-
	5-+ Medications	1.35 (1.27—1.43)	1.75 (1.65—1.86)	1.50 (1.41—1.59)	-
	Missing	1.29 (1.15—1.44)	1.42 (1.27—1.58)	1.34 (1.20—1.50)	-
MENTAL HEALTH					
Mental illness	Neither depression nor anxiety	reference	reference	reference	-
	Self-reported depression or anxiety	1.01 (0.97—1.05))	1.09 (1.05—1.13)	1.04 (1.00—1.08))	-
	Missing	1.10 (1.06—1.15)	1.12 (1.08—1.17)	1.12 (1.07—1.16)	-
HEALTH-RELATED BEHAVIORS					
BMI	Underweight	reference	reference	reference	-
	Healthy weight	0.85 (0.76—0.95)	0.79 (0.71—0.88)	0.81 (0.73—0.91)	-
	Overweight	0.79 (0.71—0.88)	0.72 (0.65—0.81)	0.75 (0.67—0.84)	-
	Obese	0.77 (0.69—0.87)	0.74 (0.66—0.82)	0.76 (0.68—0.85)	-
	Missing	0.85 (0.76—0.96)	0.84 (0.75—0.94)	0.85 (0.76—0.96)	-
Non-smoking	No	reference	reference	reference	-
	Yes	0.79 (0.74—0.83)	0.77 (0.73—0.81)	0.76 (0.72—0.81)	-
	Missing	0.86 (0.72—1.03)	0.93 (0.78—1.11))	0.90 (0.76—1.08))	-
Safe alcohol intake	No	reference	reference	reference	-
	Yes	1.06 (1.02—1.10)	1.11 (1.07—1.16)	1.09 (1.05—1.13)	-
	Missing	1.14 (1.04—1.24)	1.33 (1.22—1.45)	1.25 (1.14—1.36)	-
FUNCTIONAL STATUS					
Self-reported health status	Excellent	reference	reference	reference	-
	Very good	1.18 (1.11—1.25)	1.28 (1.21—1.36)	1.24 (1.17—1.32)	-
	Good	1.32 (1.24—1.40)	1.71 (1.61—1.81)	1.57 (1.48—1.66)	-
	Fair	1.61 (1.51—1.73)	2.72 (2.55—2.90)	2.35 (2.20—2.51)	-
	Poor	2.13 (1.94—2.34)	4.76 (4.37—5.19)	3.89 (3.56—4.24)	-
	Missing	1.44 (1.31—1.58)	2.39 (2.20—2.59)	2.09 (1.92—2.27)	-
Health-Related Quality of Life	No limitation	reference	-	-	-
	Minor limitation	0.96 (0.91—1.02)	-	-	-
	Mild limitation	1.10 (1.04—1.16)	-	-	-
	Moderate limitation	1.27 (1.21—1.34)	-	-	-
	Severe limitation	1.66 (1.57—1.75)	-	-	-

Predictive risk modelling scenario		Model 1	Model 2	Model 2 alt	Model 3
	Missing	1.31 (1.23—1.39)	-	-	-
Falls History	**0 Falls**	**reference**	-	-	-
	1 Fall	1.07 (1.01—1.12)	-	-	-
	2+ Falls	1.15 (1.10—1.20)	-	-	-
	Missing	1.07 (1.00—1.15)	-	-	-
PRIOR HEALTH SERVICE UTILIZATION					
Previous hospitalization (specify look-back)	**None**	**reference**	-	-	**reference**
	1	0.95 (0.91—1.00)	-	-	0.94 (0.90—0.99)
	2	1.25 (1.16—1.35)	-	-	1.29 (1.20—1.39)
	3+	2.23 (2.03—2.45)	-	-	2.44 (2.22—2.68)
Previous ED use (specify look-back)	**None**	**reference**	-	-	**reference**
	1	1.66 (1.58—1.74)	-	-	1.80 (1.71—1.89)
	2	2.13 (1.96—2.32)	-	-	2.39 (2.20—2.60)
	3	2.18 (1.88—2.53)	-	-	2.54 (2.20—2.94)
	4+	3.24 (2.73—3.84)	-	-	3.79 (3.20—4.48)
Prior acute admission via ED	**Not via ED**	**reference**	-	-	**reference**
	All episode in ED	1.23 (1.11—1.36)	-	-	1.20 (1.08—1.32)
	Admitted via ED	1.28 (1.20—1.37)	-	-	1.26 (1.18—1.35)
	N/S or N/A	0.84 (0.80—0.89)	-	-	0.73 (0.69—0.77)
	No Admission	0.69 (0.66—0.73)	-	-	0.56 (0.53—0.59)
LOS of prior acute admission	**0-2 days**	**reference**	-	-	**reference**
	3-7 days	1.13 (1.06—1.20)	-	-	1.22 (1.15—1.30)
	8-14 days	1.25 (1.14—1.36)	-	-	1.40 (1.28—1.53)
	15-30	1.18 (1.05—1.32)	-	-	1.40 (1.24—1.56)
	over 30 days	1.16 (0.99—1.37)	-	-	1.30 (1.10—1.53)
PRIMARY CARE ACCESSIBILITY					
Prior GP care	**0 visits**	**reference**	-	**reference**	-
	1-3 visits	0.88 (0.82—0.95)	-	0.80 (0.75—0.86)	-
	4-5 visits	0.99 (0.91—1.06)	-	0.94 (0.87—1.01)	-
	6-11 visits	1.17 (1.09—1.25)	-	1.23 (1.15—1.31)	-
	12+ visits	1.60 (1.49—1.72)	-	2.04 (1.91—2.19)	-

† The intercept estimate is the estimated odds of the outcome (hospital readmission within 12 months) when all predictor variables equal their reference values. All other estimates are odds ratios. Estimates in brackets are 95% confidence intervals.

STROBE (Strengthening The Reporting of OBservational Studies in Epidemiology) Checklist

A checklist of items that should be included in reports of observational studies. You must report the page number in your manuscript where you consider each of the items listed in this checklist. If you have not included this information, either revise your manuscript accordingly before submitting or note N/A.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Section and Item	Item No.	Recommendation	Reported on Page No.
Title and Abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	2
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2-3
Introduction			
Background/Rationale	2	Explain the scientific background and rationale for the investigation being reported	5-6
Objectives	3	State specific objectives, including any prespecified hypotheses	7
Methods			
Study Design	4	Present key elements of study design early in the paper	7-15
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	7-8
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up	N/A
		Case-control study—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls	N/A
		Cross-sectional study—Give the eligibility criteria, and the sources and methods of selection of participants	2, 8
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed	N/A
		Case-control study—For matched studies, give matching criteria and the number of controls per case	N/A
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	10-13

Section and Item	Item No.	Recommendation	Reported on Page No.
Data Sources/ Measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	10-13
Bias	9	Describe any efforts to address potential sources of bias	14
Study Size	10	Explain how the study size was arrived at	8,15
Quantitative Variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	10-13
Statistical Methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	14
		(*b*) Describe any methods used to examine subgroups and interactions	14-15
		(*c*) Explain how missing data were addressed	9
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	N/A N/A N/A
		(*e*) Describe any sensitivity analyses	19
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	15
		(b) Give reasons for non-participation at each stage	15
		(c) Consider use of a flow diagram	N/A
Descriptive Data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	Appendix C
		(b) Indicate number of participants with missing data for each variable of interest	Appendix C
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	N/A
Outcome Data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	N/A
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	N/A
		Cross-sectional study—Report numbers of outcome events or summary measures	Appendix C

Section and Item	Item No.	Recommendation	Reported on Page No.
Main Results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	15-19
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A
Other Analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	19
Discussion			
Key Results	18	Summarise key results with reference to study objectives	20-24
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	4, 24
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	20-24
Generalisability	21	Discuss the generalisability (external validity) of the study results	4
Other Information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	25

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Once you have completed this checklist, please save a copy and upload it as part of your submission. DO NOT include this checklist as part of the main manuscript document. It must be uploaded as a separate file.