IHACPA

National Pricing Model 2025–26

Risk adjustments for avoidable hospital readmissions

Technical Specifications

March 2025

National Pricing Model 2025–26 – Risk adjustments for avoidable hospital readmissions – Technical Specifications – March 2025

Contents

Table of acronyms and abbreviations

Acronym/abbreviation	Description
AHR	Avoidable hospital readmission
APC NMDS	Admitted patient care national minimum data set
AR-DRG	Australian refined diagnosis related group
GBDT	Gradient boosting decision tree
COAG	Council of Australian Governments
COF	Condition onset flag
GWAU	Gross weighted activity unit
HAC	Hospital acquired complication
ICD-10-AM	International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification
ICU	Intensive care unit
IHACPA	Independent Health and Aged Care Pricing Authority
IHI	Individual Healthcare Identifier
LHN	Local hospital network
MDC	Major diagnostic category
NEC	National efficient cost
NEP	National efficient price
NHCDC	National hospital cost data collection
NMDS	National minimum data set
NWAU	National weighted activity unit
PRC	Precision recall curves
ROC	Receiver operating characteristic
SEIFA	Socio-economic indexes for areas

Glossary of terms

Term	Description
AHR risk adjustment model	This predicts the probability of a specific AHR occurring within an episode of care. It consists of a series of logistic regression models, one for each AHR.
AHR risk adjusted NWAU	The NWAU of the index episode of care minus the dampening NWAU from the readmission episode.
AHR risk adjustment	The cost adjustment applied to the index admission for a readmission. This is measured in NWAU and is equal to the readmission episode base price weight multiplied by the dampening factor.
Complexity group	This refers to the grouping of episodes within a single AHR into low, moderate, and high complexities.
Complexity bounds/Complexity group cutoff thresholds	The threshold value of complexity score which separates episodes within a single AHR into low, moderate, and high complexity groups.
Complexity points	The numeric output of the AHR level models, prior to any manipulation.
Complexity score	The transformed logarithm of outputs from the AHR model gradient boosted decision tree (the complexity points), at the AHR level.
Condition onset flag	This flag is used to identify whether a diagnosis occurred during an episode of admitted care.
Dampening factor	The percentage total of the readmission NWAU removed from the index episode. This is based on the relative frequency of different episodes with complexities in the 1 to 100 range used in AHR modelling.
Gradient Boosting Decision Tree	A combined sequence of decision trees iteratively modelled on the residuals of previous decision trees.
Logistic regression	A model of the log-odds of an event as a linear combination of independent variables
Readmission category/condition	The avoidable hospital readmission category that a readmission episode is identified as. Categories AHR1 to AHR12 are currently identified.
Risk factor	A variable which is associated with the probability of a specific AHR occurring within an episode of care.
The Commission	The Australian Commission on Safety and Quality in Health Care

1. Introduction

1.1 Purpose

This document has been produced as an accompaniment to the National Efficient Price 2025-26 (NEP25) Determination. It provides the technical specifications for how the Independent Health and Aged Care Pricing Authority (IHACPA) developed the avoidable hospital readmissions (AHRs) funding approach and risk adjustment methodology, which has been in effect since 1 July 2021. It also provides guidance to hospitals, local hospital networks (LHNs) and state and territory health authorities on how to apply these to hospital activity.

1.2 Background

In April 2016, all Australian governments signed a Heads of Agreement that committed to improving the health outcomes of all Australians and ensuring the sustainability of the Australian health system. The Heads of Agreement required governments, in conjunction with IHACPA and the Commission, to develop 'a comprehensive and risk-adjusted model to integrate safety and quality into hospital pricing and funding' for 'a set of agreed hospital acquired conditions' to improve health outcomes and decrease avoidable demand for public hospital services.

In May 2020, all Australian governments signed the new Addendum to the National Health Reform Agreement (the Addendum), under which IHACPA is required to develop a pricing model for AHRs, for implementation from 1 July 2021, following approval from the Council of Australian Governments (COAG) Health Council.

The implementation of pricing and funding for safety and quality has been introduced on a staged basis. Funding adjustments related to sentinel events were introduced in July 2017, followed by funding adjustments for HACs in July 2018. In July 2019, IHACPA commenced a shadow period to analyse funding options for reducing avoidable hospital readmissions.

The Commission was tasked with developing and maintaining a nationally consistent definition of avoidable hospital readmissions. The list of clinical conditions considered as avoidable hospital readmissions was approved by the Australian Health Ministers' Advisory Council (AHMAC) in June 2017.

AHR adjustment scope

The AHR shadow period investigated the following funding options across hospital, LHN and jurisdiction levels:

- Option one: Deduct the price of the readmission episode from the index episode (funding impact during the shadow period: 0.64%)[1]

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[1] Consultation Paper on the Pricing Framework for Australian Public Hospital Services 2021–22 | Resources | IHACPA

- Option two: Combine the index and readmission episodes and recalculate the price of the combined episode (funding impact during the shadow period: 0.63%)[1]
- Option three: Adjust funding at the hospital level where actual rates of avoidable readmissions exceed expected rates of avoidable readmissions (funding impact during the shadow period: 0.15%).[1]

These options are discussed in the 'Consultation paper for the pricing framework for Australian public hospital services 2021-22'. IHACPA provided detailed reports to its Jurisdictional Advisory Committee (JAC), Technical Advisory Committee (TAC) and Clinical Advisory Committee (CAC) on the activity and funding impacts of the funding options. Following analysis and stakeholder feedback, option one, the deduction of the cost of the readmission episode from the index episode, was selected and has been continued to date.

Following reporting and consultation, the decision was made to apply AHR deductions at the jurisdiction level using the available Medicare PIN as a unique patient identifier until a nationally consistent Individual Healthcare Identifier (IHI) is available. This decision reflects the reporting and consultation outcomes which note that identifying readmissions at a jurisdictional level allow for the best coverage of readmission episodes and a more robust validation of available data. This option was the preference for the majority of advisory sources, except for CAC, which supported option three, that is, adjustment at the hospital level. The decision to use option one was taken in light of the lower bias it showed against regional and remote hospitals compared to other options.

1.3 Risk adjustment for avoidable hospital readmissions

The initial risk adjustment model used in development of the AHRs pricing model was a logistic regression model. This was similar to the hospital acquired complications (HACs) risk adjustment model. This model showed poor fit to the readmission data. To improve the model, IHACPA tested a new risk adjustment model based on gradient boosting decision trees. This model showed substantial improvements in performance and better fit to data than the previous logistic regression model.

Based on this, AHRs uses a gradient boosting decision tree (GBDT) model. This model has been endorsed by the University of Melbourne and IHACPA has implemented this model since the start of AHR risk adjustment. Each NEP year, a risk adjustment model is created for each readmission category, which assigns the risk of being readmitted for each episode of care, based on 'feature importance' (these features being the most clinically significant and best performing risk factors).

Changes to the AHR risk adjustment model for NEP25

During development of NEP25, a shift was made to strictly separate model training and testing datasets during the AHR modelling process. This is a standard approach to combat overfitting.

Additionally, minor edits were made to ICD-10-AM codes in preparation for 13th edition in consultation with stakeholders and clinicians.

The reporting of sex and gender are changing in a number of jurisdictions and may take years to settle nationally. IHACPA will review the continued utility of these variables in respect of the modelling during future cycles. To maintain model stability for NEP25 it was necessary to backfill missing values for the sex variable using gender as a proxy for one jurisdiction.

1.4 Treatment of transfer episodes

The Commission initially developed the specification for a hospital level approach using facility-specific identifiers, leading to transfers not being flagged as readmissions. However, during IHACPA's assessment of funding impacts with an expanded scope, episodes where patients were transferred elsewhere after the index admission were being flagged as a readmission.

Due to this, IHACPA will continue utilising the definition and specifications developed by the Commission, but will trim transfer episodes from the readmissions. IHACPA will also provide data to the jurisdictions indicating how many episodes are affected and the specific episodes trimmed from the readmission counts.

1.5 Risk factors

A set of risk factors has been developed for each individual readmission category in the risk adjustment model. This means each readmission category has a tailored risk adjustment model based on risk factors that are highly relevant to the readmission condition. The risk factors for each readmission category were selected based on clinical relevance and statistical performance, using the feature importance breakdowns. The risk factors are discussed further in Section 5.3.

2. Avoidable Hospital Readmissions (AHRs)

2.1 Definition of an AHR

The Commission convened a working group in late June 2019 to develop a nationally consistent definition for avoidable hospital readmissions. The Commission adopted the following working definition:

> An avoidable hospital readmission occurs when a patient who has been discharged from hospital (index admission) is admitted again within a certain time interval, and the readmission:
>
> 1. is clinically related to the index admission, and;
>
> 2. has the potential to be avoided through improved clinical management and/or appropriate discharge planning and follow-up in the index admission, and;
>
> 3. is measurable through coded data generated from the patient medical record.

The above definition has been presented to AHMAC and, pending endorsement, will be used by IHACPA to define avoidable hospital readmissions.

2.2 List of AHRs

Unplanned hospital readmissions are a measure of potential issues with the quality, continuity and integration of care provided to patients during or subsequent to their original hospital admission (the index admission).

In June 2017, AHMAC approved the list of avoidable hospital readmissions developed by the Commission. The Commission released Version 2.0 of the list in May 2022. Table 1 presents the AHMAC approved list of avoidable hospital readmissions and readmission diagnoses, together with the condition-specific readmissions intervals.

The condition-specific readmission intervals have been developed by the Commission, with input from a panel of clinical and consumer experts.

If a patient with a readmission condition presents at hospital in a timeframe that exceeds the condition-specific readmission interval, this episode is not considered to be an avoidable hospital readmission.

Table 1: List of avoidable hospital readmissions and readmission intervals

Readmission condition	Readmission diagnosis	Readmission interval
1. Pressure injury	Stage III ulcer	14 days
	Stage IV ulcer	7 days
	Unspecified decubitus and pressure area	14 days
	Unstageable pressure injury	14 days
	Suspected deep tissue injury, depth unknown	14 days
2. Infections	Urinary tract infection	7 days
	Surgical site infection	30 days
	Pneumonia	7 days
	Blood stream infection	2 days
	Central line and peripheral line associated blood stream infection	2 days
	Multi-resistant organism	2 days
	Infection associated with devices, implants and grafts	90 days
	Infection associated with devices, implants and grafts in genital tract or urinary system	30 days
	Infection associated with peritoneal dialysis catheter	2 days
	Gastrointestinal infections	28 days
	Other high impact infections	2 days
3. Surgical complications	Postoperative haemorrhage/haematoma	28 days
	Surgical wound dehiscence	28 days
	Anastomotic leak	28 days
	Cardiac vascular graft failure	28 days
	Pain following surgery	14 days
	Other surgical complications	28 days
4. Respiratory complications	Respiratory failure including acute respiratory distress syndromes	21 days
	Aspiration pneumonia	14 days
	Pulmonary oedema	30 days
5. Venous thromboembolism	Venous thromboembolism	90 days

Readmission condition	Readmission diagnosis	Readmission interval
6. Renal failure	Renal failure	21 days
7. Gastrointestinal bleeding	Gastrointestinal bleeding	2 days
8. Medication complications	Drug related respiratory complications/depression	2 days
	Hypoglycaemia	4 days
	Movement disorders due to psychotropic medications	14 days
	Serious alteration to conscious state due to psychotropic medication	14 days
9. Delirium	Delirium	10 days
10. Cardiac complications	Heart failure	30 days
	Ventricular arrhythmias and cardiac arrest	30 days
	Atrial tachycardia	14 days
	Acute coronary syndrome including unstable angina, STEMI and NSTEMI	30 days
Other	11. Constipation	14 days
	12. Nausea and vomiting	7 days

2.3 Identification of AHRs

An AHR is identified using a combination of International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM) codes, allowable readmission periods, and exclusion criteria. Exclusion criteria are based on the AHR specification released by the Commission. The latest AHR specification is available on the Commission's website.[2]

For modelling AHRs during NEP25, AHRs were identified using ICD-10-AM 12th edition. This is the subsequent edition to that which was used during NEP24. Since data sets that include earlier ICD-10-AM edition codes are still in use during NEP25, the ICD-10-AM 10th and 11th edition codes used in these data sets were forward cast to ICD-10-AM 12th edition for AHR identification in NEP25.

AHR inclusion and exclusion criteria

A readmission is deemed to be an avoidable hospital readmission if:

- the index and readmission separations meet their respective service (Table 2) or index/readmission (Table 3) exclusion criteria;

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[2] https://www.safetyandquality.gov.au/our-work/indicators/avoidable-hospital-readmissions

- the readmission has a principal diagnosis on the 'readmission codes' list (and/or an additional diagnosis where specified);
- the readmission meets any additional criteria (where specified); and
- the interval between the index admission and readmission (in days) is less than or equal to the interval specified, i.e.;

> ⓘ   The date of readmission for an AHR must be within an allowed, AHR-level, interval of the index episode:
>
> *date of admission (of readmission) – date of separation (of index admission) ≤ AHR interval*

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Table 2 summarises the services that are included and excluded for AHRs based on the Commission's advice.

> ⚠   In response to stakeholder feedback, IHACPA made the decision to exclude transfer episodes from AHR adjustment. The Commission's exclusion criteria in relation to transfer episodes was developed based on hospital-level readmissions.

Table 2: Scope of included and excluded services for avoidable hospital readmissions.

	Service scope for avoidable hospital readmissions
Included services	All relevant acute admitted episodes[3] in activity based funded (ABF) hospitals comprising: Episodes with an urgency status of emergency.
Excluded services	Exclusions comprise of: - Any readmissions where the index admission had a separation mode of discharged against medical advice. - Index admissions and readmissions for oncology, haematology, chemotherapy, dialysis, neonatal care and palliative care. - Readmissions for child birth. - Transfer episodes where previously classed as a readmission (i.e. a transfer from the index admission facility to a secondary facility within the same course of care).

Table 3 outlines the complete list of exclusion criteria, based on the Commission's advice, for the list of conditions that are considered avoidable hospital readmissions.

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[3] Relevant acute admitted episodes comprise episodes with one or more of the readmission conditions in the list of Avoidable Hospital Readmissions and the readmission interval is less than or equal to the condition specific timeframes specified in this list.

Table 3: Complete list of exclusion criteria for avoidable hospital readmissions.

Index admission	Readmission
Exclude separations with ANY of the following: • Multi-purpose services and Mothercraft facilities • Admitted for same day and overnight chemotherapy and dialysis (AR-DRG equal to R63Z, L61Z, L68Z, with admission date equal to separation date) • Admitted for oncology or haematology (any diagnosis: C00 to D89) • Admitted for neonatal care (Care type: 7) • Admitted for palliative care (Care type: 3) • Hospital boarder, organ procurement, unqualified newborns (Care types 9, 10, or 7.3) • Not discharged alive (mode of separation starts with 8) • Discharged against medical advice (mode of separation starts with 6)	Exclude separations with ANY of the following: • Multi-purpose services and Mothercraft facilities • Admitted for same day and overnight chemotherapy and dialysis (AR-DRG equal to R63Z, L61Z, L68Z, with admission date equal to separation date) • Admitted for oncology and haematology (any diagnosis: C00 to D89) • Admitted for neonatal care (Care type: 7) • Admitted for child birth (Adjacent AR-DRG equal to O01, O02, or O60) • Admitted as a transfer from a different facility within the same course of care • Non-acute care type (Care type not 1) • Non-emergency admission (Urgency status not equal to 1)

3. Data preparation

3.1 Datasets

The development of the risk adjustment model and funding adjustments for AHRs used the following data:

- Twelve months activity data for 2019–20
- Twelve months activity data for 2020–21
- Twelve months activity data for 2021–22
- Nine months activity data for 2022–23.

The sample of data used to fit the risk model includes only nine months of activity data for 2022-23 to avoid any potential bias in the training sample, as the longest readmission interval is 90 days. For the purposes of the funding calculations, the hospital list from the most recent NEP Determination was used to define ABF hospitals and their characteristics.

3.2 Data trimming

The following rules were implemented to clean the data and identify whether an episode was to be trimmed:

- Episodes with no associated Medicare PIN were trimmed as it is not possible to identify readmission episodes.
- Episodes with a missing separation date were trimmed as non-discharged episodes do not have complete ICD-10-AM/ACHI code arrays.
- Episodes with a shared Medicare PIN but inconsistent birth date or sex were trimmed to ensure that only episodes with consistent patient identifiers were considered when flagging readmissions.
- Concurrent episodes were trimmed where the same patient had multiple concurrent admitted episodes, with only the episode with the earliest admission date and the readmission episode being kept. This was to prevent inconsistent flagging of potential readmission episodes.
- Episodes that did not meet both the index episode denominator criteria and the readmission episode denominator criteria shown in Table 3 were trimmed as they were deemed irrelevant to the model.

A summary of the episodes trimmed for the 2019-20 to 2022-23 data years is presented in Table 4.

Table 4: Summary of trimmed episodes for the 2019-20, 2020–21, 2021–22 and 2022–23 activity data.

	Activity Data Year			
Trim type	**2019-20**	**2020-21**	**2021-22**	**2022-23**
Total Episodes	6,923,469	7,245,126	6,972,918	7,239,588
Trimming due to:				
Missing Medicare PIN	471,975	488,389	566,126	474,027
Missing separation date	-	-	-	-
Not unique Medicare PIN	246,375	246,479	231,015	232,628
Concurrent episodes:				
Reasonable concurrent episodes	241	288	507	415
Same establishment	312	134	251	451
Overlapping episodes	415	606	982	955
Engulfed episode	6,295	9,115	8,142	8,311
Cannot be index or readmission episode	2,471,698	2,601,048	2,426,753	2,591,361
Total episodes remaining (untrimmed)	**3,726,158**	**3,899,067**	**3,739,142**	**3,931,440**
% of episodes trimmed from public hospitals	**10.48%**	**10.28%**	**11.57%**	**9.90%**

Medicare Pin Quality

Table 5 shows the quality of the Medicare PIN reporting for 2019–20, 2020–21, 2021–22 and 2022–23 for admitted episodes of care. The percentage of good quality Medicare PIN data for each year is measured based on the percentage of episodes with consistency in the birth date or sex of the episodes of care to which it has been attached, and is measured as a step in trimming the AHR modelling datasets. Inconsistency in birth date or sex refers to differences in the birth date or sex of any episodes with a shared Medicare PIN across the data years used for modelling AHRs. In the case that there is an inconsistency, all episodes with the identified Medicare PIN are trimmed to ensure modelling is performed on the best possible quality data.

During NEP25, due to changes brought about by introduction of the gender variable, it was necessary to backfill missing values for the sex variable using gender as a proxy for one jurisdiction to maintain model stability. For all jurisdictions in all years assessed, the figures do not appear to indicate systemic reporting errors.

Table 5. Quality of Medicare PIN reporting.

State/Territory	Percentage of good quality Medicare PIN			
	2019-20	2020-21	2021-22	2022-23
NSW	95.6%	96.1%	95.9%	96.3%
Vic	93.5%	93.7%	93.8%	94.2%
Qld	98.2%	98.2%	98.2%	98.2%
SA	97.7%	97.8%	97.8%	97.9%
WA	97.7%	97.7%	98.5%	97.8%
Tas	99.6%	99.6%	99.6%	99.5%
NT	96.3%	96.2%	96.2%	96.4%
ACT	96.8%	95.8%	96.8%	96.4%
National	**96.2%**	**96.4%**	**96.4%**	**96.6%**

4. Distribution of AHRs

4.1 AHR counts by admission year

Analysis of the highest presenting clinical conditions responsible for readmissions provides valuable insight to why readmission episodes are occurring.

Table 6 outlines the AHMAC approved list of avoidable hospital readmissions and corresponding number of readmissions for the years 2019–20, 2020–21, 2021–22 and the first nine months of 2022–23.

Table 6: List of avoidable hospital readmissions and number of readmissions over a four year period.

Readmission Condition	Number of readmissions				
	2019-20	2020-21	2021-22	2022-23[4]	Total
1. Pressure injury	88	111	91	76	366
2. Infections	16,191	15,581	15,461	12,094	59,327
3. Surgical complications	8,773	9,749	7,555	6,002	32,079
4. Respiratory complications	2,043	2,224	2,228	1,740	8,235
5. Venous thromboembolism	2,833	3,136	2,775	2,120	10,864
6. Renal failure	1,618	1,645	1,518	1,204	5,985
7. Gastrointestinal bleeding	360	374	319	269	1,322
8. Medication complications	1,025	980	968	753	3,726
9. Delirium	1,658	1,608	1,900	1,412	6,578
10. Cardiac complications	15,450	14,944	13,217	10,070	53,681
11. Constipation	2,814	2,898	2,330	1,851	9,893
12. Nausea and vomiting	1,476	1,651	1,412	1,064	5,603
% of untrimmed episodes	1.6%	1.5%	1.4%	1.4%	1.5%

Infections is the leading readmission condition, with 59,327 readmissions over the observation period, followed closely by cardiac complications with 53,681 readmission episodes. These figures

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[4] Note that the 2022-23 readmission counts may, in part, be lower due to the fact that only the first nine months of data were considered. The observation period in 2022-23 is restricted because the longest readmission interval is 90 days.

are useful in assisting clinicians with the development of strategies to reduce or prevent avoidable hospital readmissions relating to specific conditions, and can be used to direct focus onto those conditions with disproportionately high rates of readmissions. The trajectory of AHRs as a percentage of total modelling records over time is shown in **Appendix A**.

5. AHR Risk adjustment model

5.1 Overview

IHACPA notes the need to balance the perspectives of both hospitals and patients when incorporating safety and quality into pricing. Hospitals that treat high-risk patients should not be disadvantaged compared to hospitals that treat fewer such patients. Likewise, high risk patients should have confidence that hospitals take all necessary actions to manage their risks and mitigate the occurrence of adverse events.

The equitable risk adjustment criterion used by IHACPA states that:

> (i) Pricing and funding approaches should balance the likelihood that some patients will be at higher risk of experiencing an adverse event while recognising that all hospitals have scope to improve safety and quality.

The history of developments and considerations during the shadow period for the AHR risk adjustment model that led to the adoption of the current model is discussed in **Appendix B**. The risk adjustment model is constructed on the premise that a patient's likelihood of experiencing a potentially avoidable hospital readmission is the same regardless of the funding option considered. Therefore, a risk adjustment model is derived for each readmission condition, which assigns the readmission complexity for each episode of care, based on selected risk factors identifiable in the National Minimum Data Set (NMDS).

The readmission complexity output of the AHR risk adjustment model is different from the probability of being readmitted. The AHR model minimizes the cross-entropy loss of the aggregated residuals of a sequence of decision trees, which leads to the model output being the minimized cross-entropy of a complex system. This should not be interpreted as the chance of an episode being a readmission (a deterministic event based on definitions from the Commission), or the chance of an index episode resulting in a readmission, as these interpretations will lead to many false positives (non-readmission episodes identified as readmissions).

In the AHR model, episodes are assigned to a 'Low', 'Moderate' or 'High' complexity group representing the complexity of an episode, based on identified risk factors. The model assigns adjustments as percentages of the total readmission episode NWAU based on these complexity groups, which are removed from the NWAU assigned to the index episode for the readmission.

5.2 Model description

The original modelling approach investigated for AHRs was based on the HACs logistic regression model. Further information on the performance and limitations that led to moving away from this

model are available in **Appendix C**. The AHR adjustment model applied uses gradient boosting decision trees (GBDTs). This is a shift away from the logistic regression model used for the HACs risk model. The shift to the GBDT model has seen a reasonable improvement in model performance due to its ability to model more complex interactions between risk factors, while reducing the possibility of 'overfitting'. Under the GBDT model, the marginal risk of each risk factor is not a constant, but depends on the combination of risk factors present in a particular episode. For example, for a given readmission category, being admitted to ICU will have a different marginal impact depending if the patient is admitted to a surgical or medical AR-DRG, and similarly for all other risk factors.

Modelling interactions between risk factors in a complex manner like this will often result in 'over-fitting' the model to the data on which it is trained, picking up natural variance present in the data and measuring it as a real effect. In AHRs, over-fitting has been reduced using the GBDT machine learning technique, which involves fitting hundreds of thousands of similar models to subsets of the same data. This allows natural variance in the modelled data to be accounted for, therefore reducing over-fitting while retaining the benefits of decision tree classification algorithms. Overfitting is still very possible in gradient boosting methods, so in NEP25 tuned model parameters were implemented to minimize this effect.

The GBDT risk adjustment model automatically determines the best aggregation for risk factors that have multiple levels. As an example, this differs from some of the five-year age brackets in the HACs risk adjustment model, which are combined for some HACs depending on manual analysis and interpretation of sample size and statistical significance testing. The GBDT model is able to filter out factors automatically and determine how to achieve the most optimal grouping for risk factors as part of constructing individual decision trees that make up the model.

Ensemble Learning

During the development of the AHR model, IHACPA investigated using decision trees as an alternative to logistic regression. The original decision tree model is discussed in Appendix C. Using a small decision tree by itself may not consider all the risk factors, due to the limited tree depth. On the other hand, fitting a much deeper or wider decision tree is undesirable because it can overfit the data, meaning that the resulting model could perfectly describe the data it is trained on, but not generalise well to the broader population. A technique that captures the benefits of decision trees while producing a more general model is called ensemble learning.

Ensemble learning models make predictions based on the combined findings of several constituent models, each of which is individually known as a "weak learner" due to its low prediction accuracy. The combination of several weak learners tends to result in a model that overtrains less, is less biased and shows less variance than the individual models making it up, while performing well on unseen data. The GBDT model implemented is one such technique and has been used in other studies to predict readmissions, with sound results. This approach fits multiple decision trees in a sequential manner (a type of ensemble learning called boosting). The first decision tree is fit to the input data using the usual decision tree method (see Appendix C), and then the subsequent trees are fit to the residuals, or errors, from the preceding model. This way, as more decision trees are fit to the errors made by the preceding tree, the model gradually gets better.

As the model adds new decision trees, it tests its performance on a validation data set which was not used to train the model (comprising 10 per cent of the training data). When the model performance stops improving with respect to this validation set, the model stops adding new decision trees and the training process is complete. This is done to prevent overfitting by adding too many decision trees to the model.

5.3 Risk factors

The AHR model assigns AHR complexity based on episode level risk factors. The methods of risk factor selection and the evaluation for the addition or removal of risk factors is discussed in **Appendix D**. IHACPA notes that risk factors for avoidable hospital readmissions were examined independently of risk factors included in the funding model for HACs, as there are additional elements of long-term patient characteristics that must be considered.

Historical risk factors

Throughout the AHR shadow period, IHACPA assessed a number of risk factors. During this assessment, Charlson comorbidity diagnostic categories and chronic condition flags (which were identified based on the presence of chronic disease category ICD-10-AM codes) were examined for inclusion in the risk factor set for AHRs. The risk factors proposed throughout the shadow period and the shadow period definitions of Charlson comorbidity and chronic disease categories are presented in **Appendix E**.

Considerations during risk factor selection

During the shadow period, stakeholders expressed concern about using risk factors that were overly statistically driven and requested clinical evaluation of the final list. IHACPA has endeavored to achieve a balance of statistical significance and clinical relevance through a literature review of other readmissions studies[5,6], and through the use of feature importance breakdowns for key risk factors associated with each readmission condition. Feature importance breakdowns are an output of the AHR risk adjustment model, where the relative statistical importance and model contribution of each risk factor can be assessed relative to that of other risk factors.

During the shadow period, IHACPA refined the list of risk factors based on stakeholder feedback, consultation with the University of Melbourne and assessment of clinical relevance using the top feature importance breakdowns to remove risk factors that did not significantly contribute to model performance and prediction of readmissions. In the previous NEP 2024-25 period (NEP24), IHACPA revised the original ICD-10-AM codes used in identifying the presence of risk factors, to make sure the most relevant advice was taken into account for ICD-10-AM 11th and 12th editions. This review was carried out in consultation with clinical, technical, and jurisdictional committees and resulted in significant changes to the codes used in identifying risk factors. The current set of ICD-10-AM codes used in identifying standalone and Charlson risk categories in avoidable hospital readmissions are presented in **Appendix F**. Note that, due to considerations below, not all of the

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[5] Min, X., Yu, B. & Wang, F. Predictive Modeling of the Hospital Readmission Risk from Patients' Claims Data Using Machine Learning: A Case Study on COPD. Sci Rep 9, 2362 (2019). https://doi.org/10.1038/s41598-019-39071-y

[6] Donzé J, Aujesky D, Williams D, Schnipper JL. Potentially Avoidable 30-Day Hospital Readmissions in Medical Patients: Derivation and Validation of a Prediction Model. JAMA Intern Med. 2013;173(8):632–638. doi:10.1001/jamainternmed.2013.3023

potential risk factors are implemented in the modelling process for every AHR model. In the NEP 2025-26 period (NEP25), IHACPA further reviewed the risk factors contained within the Charlson comorbidity flags and chronic condition flags to identify clinically insignificant flags, leading to a small number of changes to capture intended ICD-10-AM codes.
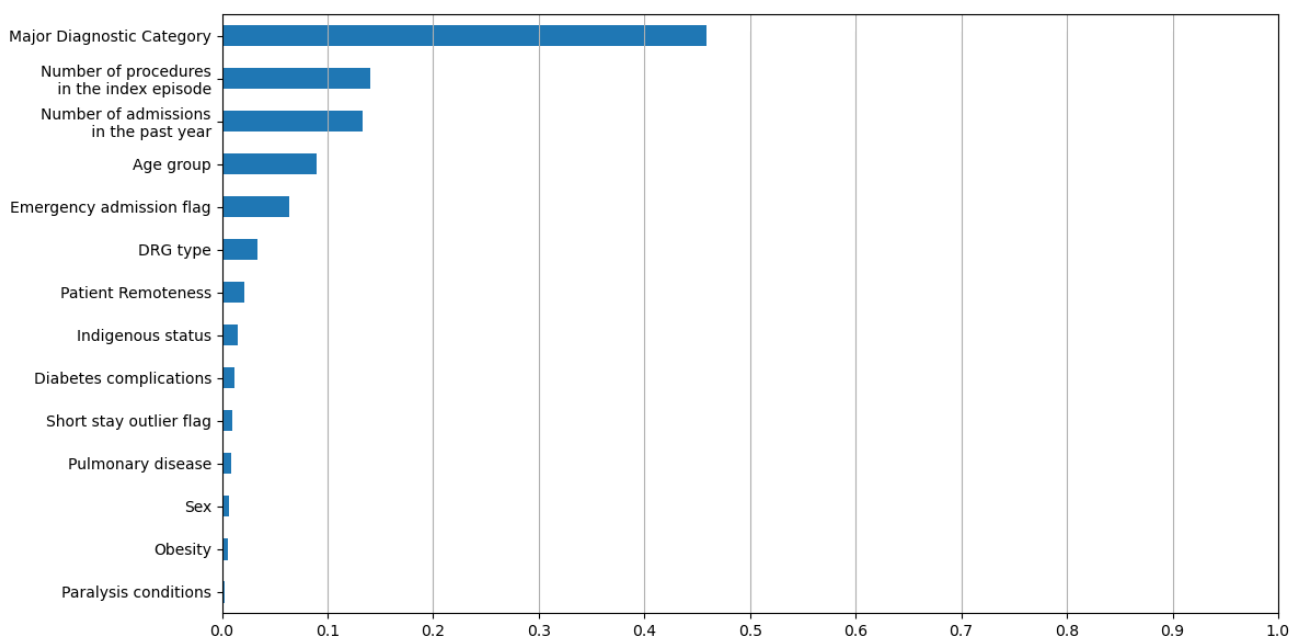
NEP25 risk factors

Risk factor determination

Percentage contribution scores from relative feature importance plots, which rank variables by their relative discriminatory power with respect to model objectives, were examined for each risk factor, at the AHR level. This provided insight into the statistical significance and impact of the modelled risk factors. IHACPA created top feature importance breakdowns for each readmission category to finalise the risk factors.

Figure 1 below shows the top feature importance breakdown for infections (AHR2; the highest presenting readmission condition over the four year period assessed). The top feature importance breakdowns of all readmission categories are provided in **Appendix G**.

Figure 1: Top features relating to infections (AHR02) vs relative feature importance.

The detailed method used to select and the process for re-assessing the risk factors for each AHR is outlined in Appendix D.

Finalised risk factors

IHACPA did not make changes to the risk factors for each readmission category for NEP25.

Table 7 lists the final risk factors used in each AHR GBDT model.

Table 7: Risk factors for each readmission category

Risk Factor	01. Pressure injury	02. Infections	03. Surgical complications	04. Respiratory complications	05. Venous thromboembolism	06. Renal failure	07. Gastrointestinal bleeding	08. Medication complications	09. Delirium	10. Cardiac complications	11. Constipation	12. Nausea and vomiting
Standalone risk flags												
Past year admissions	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age group	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Major Diagnostic Category	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Procedure count	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AR-DRG type		✓	✓			✓	✓	✓	✓	✓	✓	✓
Drug use									✓			
Transfer admission								✓				
Emergency admission	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ICU					✓				✓			
Gender		✓		✓	✓	✓	✓		✓		✓	✓
Indigenous	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Low length of stay		✓			✓							
Malnutrition												✓
Pacemaker	✓											
Patient remoteness	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Post transplant						✓						
Charlson comorbidity flags												
Acute myocardial function										✓		
Congestive heart failure						✓				✓		
Diabetes				✓				✓				
Diabetes complications		✓				✓		✓		✓		
Dementia				✓					✓			
Pulmonary disease		✓			✓							
Renal disease						✓		✓		✓		
Chronic condition flags												
Arthritis and osteoarthritis												✓
Cerebral palsy				✓							✓	✓
Chronic heart failure										✓		
Chronic kidney disease						✓						
Chronic respiratory failure				✓								

Risk Factor	01. Pressure injury	02. Infections	03. Surgical complications	04. Respiratory complications	05. Venous thromboembolism	06. Renal failure	07. Gastrointestinal bleeding	08. Medication complications	09. Delirium	10. Cardiac complications	11. Constipation	12. Nausea and vomiting
Chronic obstructive pulmonary disease	✓			✓								
Crohns disease											✓	✓
Depression					✓				✓			
Disorder of intellectual											✓	
Downs syndrome			✓									
Hypertension					✓	✓	✓					
Ischaemic heart disease					✓					✓		
Obesity		✓			✓							
Osteoporosis							✓					
Severe liver disease						✓						
Spina bifida	✓											
Paraplegia	✓	✓		✓								
Total number of risk factors:	11	14	9	13	16	16	11	12	13	14	12	13

5.4 Assessment of model performance

IHACPA has generally used receiver operating characteristic (ROC) curves to measure the performance of the HAC and early iterations of the AHR risk adjustment model.

However, ROC curve metrics do not present the whole picture about the performance of models, due to imbalance in the data. That is, the ROC curve metrics alone may not clearly reflect significant changes in model performance where the number of episodes with no subsequent avoidable hospital readmissions is far greater than the number of episodes with an avoidable hospital readmission. To account for this, IHACPA has used precision recall curves (PRC), which are more informative that ROC curves on highly unbalanced data, alongside ROC curves in evaluating readmissions risk modelling.

## Receiver operating characteristic curve

The ROC curve is an analytical method that can be used to evaluate a model's ability to predict a binary outcome. In the context of the AHR risk adjustment model, we seek to evaluate the ability of this model to predict the occurrence of an AHR.

The ROC curve is a parametric plot of the true positive rate (TPR) versus the false positive rate (FPR) of the model where:

a) the TPR is the proportion of observations that are correctly predicted to be positive out of all positive observations; that is, how well the model correctly predicts the occurrence of an AHR in an episode.

b) the FPR is the proportion of observations that are incorrectly predicted to be positive out of all negative observations; that is, how often does the model incorrectly predict the occurrence of an AHR for episodes which don't have an AHR.

The ROC graph plots both parameters against a theoretical threshold varied between 0 and 1 to illustrate the tradeoff between TPR and FPR at different threshold values. An example ROC plot is provided in Figure 2.

Figure 2: Example of ROC curves
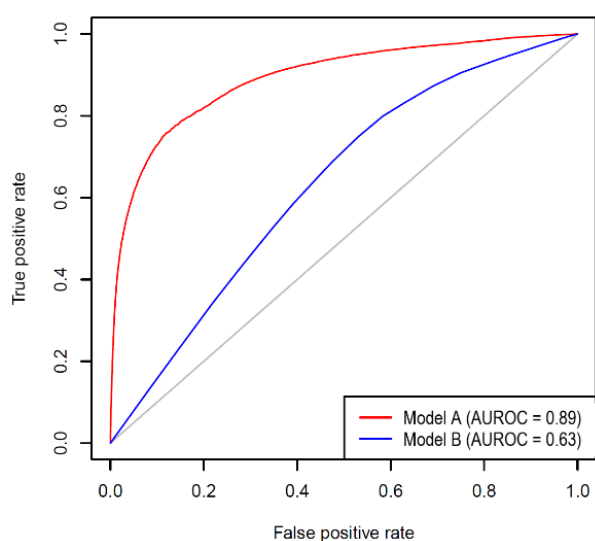
This example plot is for a general system, rather than the AHR model itself, and is purely explanatory. A ROC curve lying on the diagonal line (grey line) is reflective of a model that performs no better than chance level (random guessing). The closer the ROC curve is to the upper lefthand corner, the better the model can discriminate between two outcomes (by maximising the TPR and minimising the FPR). With reference to Figure 2, it shows that Model A (red line) performs better than Model B (blue line). In the context of the AHR risk adjustment model, this would mean that Model A is better at predicting the occurrence of a true positive AHR, with lower change of predicting a false positive AHR, in an admitted episode of care than Model B.

The area under the ROC curve (AUROC) provides an aggregate measure of the performance of the model across all the thresholds, and its value ranges between 0 and 1. A model that will predict 100% of categories wrong has an AUROC of 0.0 and a model which predicts all positive classes with 100% accuracy has an AUROC of 1.0. A model with an AUROC of 0.5, which will predict 50% of categories correctly (also referred to as the baseline) is represented by the grey diagonal line in the graph. In Figure 2, Model A has a higher AUROC than Model B which indicates that the former model performs better than the latter model.

The issue with using the ROC curve to assess model performance on imbalanced data is that the rates being compared have different denominators, that is;

$$TPR = \frac{true\ positives}{all\ positives}$$

$$FPR = \frac{false\ positives}{all\ negatives}$$

In each of the AHR models, the number of negatives (episodes with no subsequent avoidable hospital readmission) used in modelling AHRs are close to 13,000,000. While the number of positives vary from around 370 for readmission category 1 (pressure injury) to 59,000 for readmission category 2 (infections) in the four years of activity data used for training during NEP25. Taking these figures into consideration and with reference to Figure 2, this effectively means that each incremental increase in the true positive rate (i.e. correctly identified AHR episodes) for a well performing model comes with a logarithmic increase in the false positive rate (i.e. number of incorrectly identified AHR episodes is initially small, but increases rapidly past a limit). Note that these figures are used for comparison of risk models only. In practice, risk models assign a probability based on the modelled objective (which is always low for a readmission), and do not use thresholds to assign definite positive/negative outcomes.

Precision recall curve

The precision recall curve (PRC) is a complement to the ROC curve. It may give additional insight compared to the ROC curve when evaluating model performance on imbalanced data.

The PRC curve is parametric plot of the precision and recall of the model where:

a) Precision is the number of true positives out of all the predicted positives, meaning the number of episodes which actually had an AHR out of those predicted to have had an AHR.

b) Recall is another name of the true positive rate and represents how successful the model is in identifying an episode with an AHR. That is, the number of AHR episodes that the model can successfully identify out of all the AHR episodes in the data set.

The PRC graph plots both parameters against a theoretical threshold varied between 0 and 1 to illustrate the tradeoff between precision and recall at different threshold values. An example PRC curve generated on the full modelling dataset is provided for AHR10 (cardiac complications) in Figure 3.
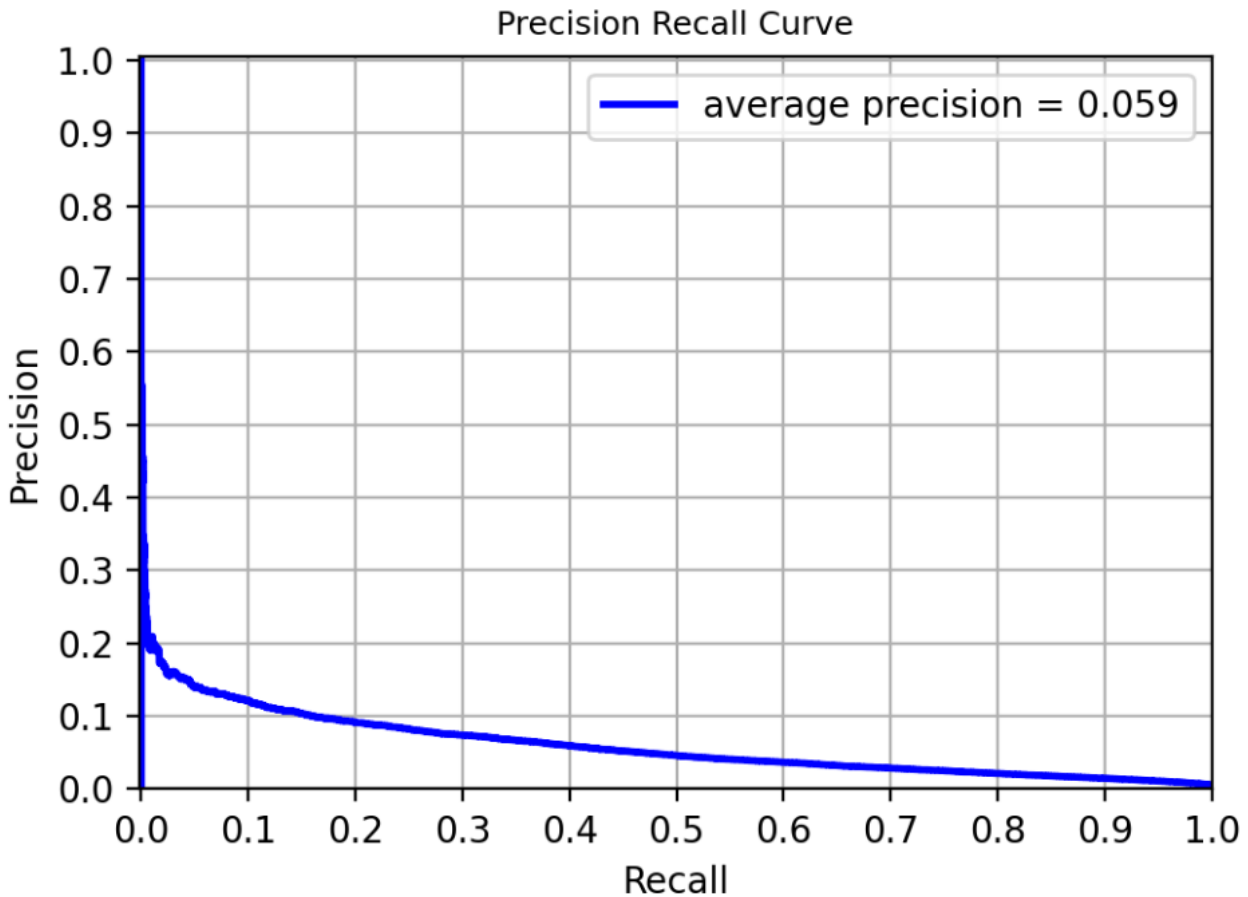
The closer the PRC curve is to the upper righthand corner, the better the model can discriminate between two outcomes (by maximising the precision and recall and thereby maximising the area under the curve).

The area under the PRC curve (AUPRC) provides an aggregate measure of the performance of the model across all thresholds. A higher AUPRC represents both high recall and high precision which is indicative of a better performing model. Generally, the AUPRC is considerably smaller in magnitude than the AUROC for the same model as the baseline is calculated as the proportion of positive observations over total observations, which is very small.

In the above case, picking a threshold which correctly identifies 20.0% of AHRs in the dataset (equivalent to 20.0% recall) gives a precision of 9.3%. In NEP25 there are approximately 54,000 AHR10 records. This means the model is predicted to return about 10,700 episodes correctly classified as leading to an avoidable hospital readmission, and around 104,400 false positives.

Training and testing data sets

Unlike the HAC risk model, which uses the same set of data for training and testing model performance, the AHR risk model uses a separate set for model testing from NEP25 onwards. This

is to minimize model overfitting. Overfitting is not a significant issue for linear models like logistic regression, however, the decision tree based model implemented for readmissions is non-linear and risks overfitting to training data, such that model performance is good on the training dataset but generalizes poorly to unseen data. To mitigate this, ROC and PRC metrics are generated on a testing dataset, comprising of 20% of the total AHR model input set, which is not used during modelling to prevent cross-contamination. Here we report performance metrics calculated on this testing dataset. This is a standard method used in the literature for testing the performance of a machine learning model.

Figure 3, above, presents the PRC plot for the best performing model, as measured by the largest PRC-AUC. In terms of area under ROC and PRC, the GBDT models perform better across all readmission categories than logistic regression models. ROC curves and PRCs for the NEP25 readmission model testing dataset are presented in **Appendix H**.

6. Episode complexity and AHR dampening

6.1 Complexity groups

The risk adjustment methodology of AHRs creates complexity groups for each AHR, with differing risk adjustments applied based on the complexity. This is based on the concept that "pricing and funding approaches should balance the likelihood that some patients will be at higher risk of experiencing an adverse event while recognising that all hospitals have scope to improve safety and quality". Each AHR is split into three complexity groups (low, moderate and high) representing the risk each patient has of experiencing an AHR. These risk categories are assigned at an AHR level and patients classified as 'high complexity' in an AHR attract a lower funding adjustment. Conversely, patients with a low risk of experiencing an AHR are classified as 'low complexity' and attract a higher funding adjustment.

> (i) The assignment of complexity group is undertaken separately for each AHR flagged in the episode, since there are separate risk adjustment models for each AHR:
>
> 1. Episode level complexity points are calculated for each AHR using that AHRs individual model and the combination of different episode level risk factors present.
>
> 2. A complexity score is calculated for each AHR in the episode through a re-scaling and bounding process that limits scores to the 1-100 range.
>
> 3. AHR level complexity scores are then compared to complexity bounds for that AHR to determine the complexity group for that AHR.
>
> This effectively means that an episode can have up to 12 different complexity scores and 12 different complexity groups assigned, one for each AHR.

To enable the assignment of complexity group for each AHR in the episode, IHACPA undertakes the following key steps on the complexity point outputs of the AHR models:

1. Converts the AHR GBDT model outputs (the complexity points) into complexity scores through a logarithmic transformation method and;
2. Determines complexity bounds for each AHR based on the distribution of complexity points for all modelling episodes. This enables assignment of a low, moderate or high complexity group for each AHR in the episode.

6.2 Complexity scores

For comparability to the HAC model, IHACPA converted the outputs of the AHR models (denoted complexity points) into complexity scores, which were then used to assign an episode into a 'Low', 'Moderate' or 'High' complexity through comparison to complexity bounds.

To calculate the complexity scores, IHACPA took the logarithm of the complexity points and calculated relative minimum and maximum scaling parameters from the 1st and 99th percentiles of log(points). This was done for each set of AHR complexity points in the modelled dataset, to produce minimum and maximum parameters for each AHR group. These minimum and maximums were then used during rescaling the model outputs to between 1 and 100, constraining results below the minimum and above the maximum (from below the 1st and above the 99th percentile) to 1 and 100, respectively. This scaled output for each AHR was the episode level complexity score.

Figure 4 shows the distribution of complexity scores for all episodes with readmissions due to cardiac complications (AHR10).

Figure 4: Readmission complexity due to cardiac complications (AHR10)
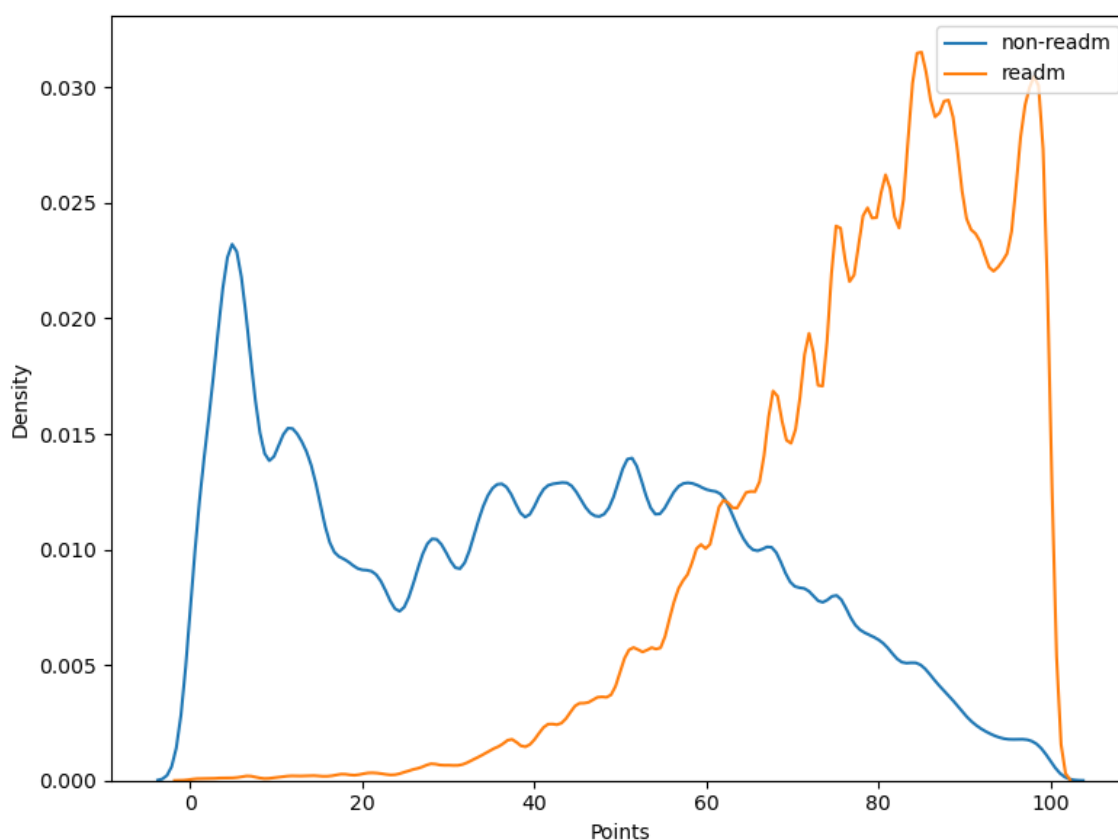
This shows the episodes resulting in readmission tend to have greater complexity than those which do not. Similar complexity distributions are provided for all readmissions in **Appendix I**.

6.3 Complexity bounds

The AHR funding adjustment (AHR dampening) is applied at an episode level by reducing the efficient price of an episode based on an incremental cost associated with the potentially avoidable hospital readmission. This is similar to the incremental cost of a HAC used for the HACs funding adjustment.

To calculate the AHR-level complexity bounds for each AHR group, the distribution of complexity points for index episodes is split into terciles. The first tercile (rounded to the nearest integer value)

is then the threshold between the low and moderate risk categories, and the second tercile is the threshold between the moderate and high risk categories.

6.4 Dampening factors

Overview

Dampening factors adjust the funding reduction for the index episode prior to an episode containing a readmission based on the risk of a patient having an AHR. Without dampening, episodes with higher complexity scores would be penalised the same amount for the same AHR as those with a lower complexity score. This goes against the policy intent of the pricing for safety and quality. Dampening factors have been developed to adjust for these differences in risk among patient profiles for different hospitals.

How do dampening factors work?

AHR adjustments reduce the NWAU assigned to an index episode based on the NWAU of a flagged readmission. Without dampening factors, this reduction would be static for each AHR, or 100% of the readmission NWAU (allowing for the caveat that the NWAU of the index admission cannot be negative, so the maximum allowable adjustment is the NWAU of the index episode). This fails to recognize the different complexity of patients that exists due to risk factors beyond the control of hospitals, and so goes against the intent of pricing for safety and quality. Dampening factors have been developed to adjust for these differences in risk among patient profiles for different hospitals.

Dampening factors take the form of a percentage score for each complexity group, at the AHR level. Low complexity patients do not receive a dampening effect on NWAU removed from the index episode, so always have a dampening factor of 1. For illustrative purposes Table 8 provides an example of how these dampening factors work in practice.

Table 8: Example – Dampening factor application

Complexity group	Index episode NWAU (a)	Readmission episode NWAU (b)	Dampening Factor (c)	Index episode NWAU received (d) = (a) - (b) x (c)
Low	1.0000	0.5000	100%	0.5000
Moderate	1.0000	0.5000	50%	0.7500
High	1.0000	0.5000	20%	0.9000

Table 8 shows that, in the explanatory case where the index episode would be assigned an NWAU of 1.0000 and the readmission episode and NWAU of 0.5000 prior to adjustment for AHRs:

a) Low complexity readmissions have a dampening factor of 100% and remove the total readmission NWAU (0.5000) from the index admission. The readmission episode is still funded in full.

b) Moderate complexity readmissions have a dampening factor of 50% and remove 50% of total readmission NWAU (0.2500) from the index admission. The readmission episode is still funded in full.

c) High complexity readmissions have a dampening factor of 20% and remove 20% of total readmission NWAU (0.1000) from the index admission. The readmission episode is still funded in full.

From this, it can be seen how the dampening factor allows the funding approach for AHRs to be risk-adjusted depending on the complexity of the episode.

> (i) One dampening factor applies per AHR that an episode has. An episode can have multiple AHR flags that apply based on its individual casemix of ICD-10-AM and procedure codes. In that case, the highest dampening factor is applied (leading to the maximum reduction of the index admission NWAU).

Calculating the AHR dampening factors

The 'incremental cost of readmission' (i.e. NWAU of the readmission episode) is used in conjunction with a dampening factor calculated based on average complexity points for each AHR category to determine the NWAU to be subtracted from the total NWAU of the index episode. The dampening factor for each risk category is calculated as the average complexity score for the low risk category, divided by the mean complexity score for that risk category, so that:

> (i)
>
> $$d_{low\_risk} = \frac{av_{score(low)}}{av_{score(low)}}$$
>
> $$d_{moderate\_risk} = \frac{av_{score(low)}}{av_{score(moderate)}}$$
>
> $$d_{high\_risk} = \frac{av_{score(low)}}{av_{score(high)}}$$
>
> Where $d_{\{category\}}$ represents the dampening factor for a category of risk, and $av_{score(category)}$ represents the mean complexity points of all episodes with an identified readmission in that category of risk. This calculation is carried out for every readmission category, so that 12 of each type of dampening factor is created.

Table 9 shows the AHR-level complexity bounds for each complexity group and the associated dampening factors applied to AHR01 to AHR12, for NEP25. These adjustments are only applied to episodes identified within the same jurisdiction. The dampening factors vary depending on the readmission category and the complexity group of the episode. For low complexity episodes, the full NWAU of the readmission episode is deducted from the index admission, where that would not exceed the NWAU of the index admission. Otherwise the NWAU of the index admission is deducted. For high complexity episodes, only a portion of the readmission NWAU is removed (e.g. 33.7% of the NWAU of the readmission episode is deducted from the NWAU of the index episode in the case of a high complexity medication complications readmission). As noted above, this is so that consideration is given to patient complexity.

Table 9: Adjustment factors for AHR01 to AHR12

	01. Pressure injury	02. Infections	03. Surgical complications	04. Respiratory complications	05. Venous thromboembolism	06. Renal failure	07. Gastrointestinal bleeding	08. Medication complications	09. Delirium	10. Cardiac complications	11. Constipation	12. Nausea and vomiting
Complexity group point thresholds												
Low	0	0	0	0	0	0	0	0	0	0	0	0
Moderate	64	63	87	58	67	56	47	71	78	76	56	59
High	80	79	94	76	78	81	73	89	90	88	75	81
Complexity group dampening factors												
Low	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Moderate	0.3940	0.5070	0.2090	0.3480	0.5140	0.2840	0.3160	0.4000	0.3860	0.4570	0.4060	0.5440
High	0.3080	0.4090	0.1960	0.2580	0.4200	0.2090	0.2050	0.3370	0.3330	0.3890	0.2990	0.4020

7. The scope of AHR adjustment

7.1 Overview

During the shadow period, IHACPA analysed a range of scope options for stakeholder consideration.

> (i) AHR adjustment scope options considered during the shadow period were adjustments being limited to episodes where the index and readmission occurred:
>
> 1. In the same establishment,
> 2. In the same LHN or
> 3. In the same jurisdiction
>
> The option to apply adjustment at the jurisdictional level was supported both by IHACPA and stakeholders, so was ultimately selected.

AHR distribution by hospital, LHN and jurisdiction

In NEP25, IHACPA has undertaken analysis of 2019-20, 2020-21, 2021-22 and 2022-23 data of all avoidable hospital readmissions identified on the trimmed readmission dataset by the location of the readmission. The analysis indicates that:

- 47.5 per cent of readmissions occurred when patients presented to the same hospital.
- 16.9 per cent of readmissions occurred in a different hospital in the same LHN.
- 35.6 per cent of readmissions occurred in a different LHN in the same state or territory.

This analysis supports continued application of the adjustment at the jurisdiction level to attain the widest coverage.

AHR distribution across financial years

In NEP25, IHACPA has undertaken analysis of 2019-20, 2020-21, 2021-22 and 2022-23 data of all avoidable hospital readmissions within or across financial years. The analysis indicates that:

- 97.3 per cent of readmissions occurred within the same financial year.
- 2.7 per cent of readmissions occurred across financial years.

7.2 Scope option for implementation

Throughout the shadow period, stakeholders were supportive of IHACPA's preference for using the widest scope possible to maximise coverage of readmission episodes. Modelling the readmissions

adjustment at a jurisdictional level was found to unequivocally be the best option as it provided the most robust data validation.

Applying funding adjustments at a jurisdictional level was also found to have a less disproportionate impact on smaller states and territories with fewer LHNs, as a large percentage of readmissions occur within the same jurisdiction. The wider scope meant a fuller coverage of readmissions.

During the shadow period, IHACPA planned to implement the AHR funding adjustment using patient Medicare PIN data to identify unique patients in the short term, with a view to shift to using an IHI available to the jurisdictions in the medium term. Medicare PIN is still to be used as a unique patient identifier for the AHR adjustment during NEP25.

8. Funding adjustment in practice

8.1 Example: General Example

IHACPA developed the following general example to assist stakeholders in applying and calculating the funding adjustment. This example has multiple AHR flags for the readmission episode to illustrate how readmission dampening works in such a case:

Index admission characteristics

The index admission occurred at Hospital A:

- The index admission had AR-DRG D12B (Other Ear, Nose, Mouth and Throat Interventions, Minor Complexity)
- The index admission was assigned 0.8395 NWAU prior to AHR adjustment

Readmission episode characteristics

The readmission episode occurred at Hospital B:

- The readmission episode fit criteria for both AHR03 (Surgical complications) and AHR09 (Delirium)
- The readmission episode had AR-DRG G66A (Abdominal Pain and Mesenteric Adenitis, Major Complexity)
- The readmission episode was assigned 0.6678 NWAU prior to AHR adjustment. This will not change since the readmission episode is not adjusted
- The complexity score for AHR03 is 93 (moderate complexity) and the complexity score for AHR09 is 98 (high complexity)

Identifying calculation parameters

- The incremental cost of the readmission is the NWAU of the readmission episode (0.6678)
- The hospitals A and B are in the same jurisdiction
- The dampening factor for AHR03 with moderate complexity is 0.2090
- The dampening factor for AHR09 with high complexity is 0.3330
- Despite having lower patient complexity for AHR03, the dampening factor for AHR09 is larger than that for AHR03
- The higher dampening factor (AHR09; 0.3330) is therefore used

The AHR adjustment calculation

NWAU reduction = incremental cost × dampening factor = 0.6678 × 0.3370 = 0.2224 NWAU

Noting that no dampening is applied to the readmission episode itself:

Readmission Funding = 0.6678 NWAU

However the index episode has the lower of either (a) the NWAU reduction amount or, if that exceeds the index admission NWAU then (b) the NWAU of the index admission; removed from it:

index episode funding = preAHR index episode NWAU - readmission funding
= 0.8395 - 0.2224
= 0.6171

So, after dampening and funding deduction for AHRs, the index episode is assigned 0.6171 NWAU

8.2 Example: Comprehensive case study

The following clinical example demonstrates the application of the avoidable hospital readmissions risk adjustment model and funding adjustment in a more comprehensive form.

1. Index admission and avoidable hospital readmission

A patient underwent an emergency appendicectomy following a diagnosis of appendicitis. At the index admission, they were assigned AR-DRG G07B (Appendicectomy, Minor Complexity) and the hospital received 1.2807 NWAU. Seven days after this patient was discharged, they were readmitted to the same hospital as they were experiencing acute pain in their lower right abdomen (AR-DRG G66B; Abdominal Pain and Mesenteric Adenitis, Minor Complexity). The price weight for the readmission was 0.2033 NWAU.

2. Application of the risk adjustment model

Pain following surgery within a readmission interval of 14 days is a readmission condition (AHR03; Surgical complications). As such, there is a funding impact to the hospital for the index admission episode, based on the risk adjusted total NWAU of the readmission episode. The funding impact from this readmission depends on the complexity group. The below complexity groups are intended as scenarios that may lead to readmission of a certain complexity, and do not necessarily reflect a blend of risk factors that lead to an episode being assigned a certain complexity group in practice.

Low complexity group	Moderate complexity group	High complexity group
At the time of admission, the patient was otherwise fit and healthy, with no comorbidities.	At the time of admission, the patient's medical history included hypertension and type 2 diabetes managed with oral medication.	At the time of admission, the patient's medical history included cirrhosis of the liver, chronic renal failure, chronic obstructive pulmonary disease and type 2 diabetes managed with insulin.

3. Calculation of the funding adjustment

Once the complexity group has been assigned, the final adjusted NWAU for the index admission can be calculated. This is determined by multiplying the NWAU of the readmission by the AHR and complexity dependent funding reduction, then subtracting the total from NWAU of the index admission.

Low complexity group	Moderate complexity group	High complexity group
As this patient was assigned to a low complexity group, funding for the index admission is reduced by 100% of the readmission episode NWAU. Funding for the index admission (1.2807 NWAU) was therefore reduced by 100.0% of 0.2033 to a total of 1.0744 NWAU for the episode of care.	As this patient was assigned to a moderate complexity group, funding for the index admission is reduced by 20.9% of the readmission episode NWAU. Funding for the index admission (1.2807 NWAU) was therefore reduced by 20.9% of 0.2033 to a total of 1.2382 NWAU for the episode of care.	As this patient was assigned to a high complexity group, funding for the index admission is reduced by 19.6% of the readmission episode NWAU. Funding for the index admission (1.2807 NWAU) was therefore reduced by 19.6% of 0.2033 to a total of 1.2409 NWAU for the episode of care.

Appendix A: AHR trajectory over time

The development of the AHR model is based on an agreement to develop, with consultation and having regards to advice from the Commission and signing parties, a pricing model for implementation from 1 July 2021. This pricing model is intended to suit the 'shared intention of the Commonwealth, State and Territory governments (the States) to work in partnership to improve health outcomes for all Australians and ensure the sustainability of the Australian health system'.[7] To measure the performance of the AHR model in reducing avoidable demand for public hospital services, the percentage of total records resulting in an AHR have been tracked since its introduction in NEP21 (Figure A1). These percentages are taken as the percentage of records with only one readmission flag, relative to the total number of modelling records for a year. This is done to avoid effects from interactions between different AHR groups. Where a data year has been used across multiple NEP cycles, the most recent one is used.

It should be noted that relative percentages for the most recent data year is not a reliable measure for trends due to containing only 9 months of data. It should additionally be noted that sudden peaks and decays outside the apparent trend of AHR frequency in the AHR1, AHR2, AHR3, AHR5, AHR8, AHR12 2020-21 and/or 2021-22 data years may be due in part to effects from the COVID-19 pandemic. Beyond these considerations, Figure A1 shows that, after initial increases or decays across the first three data years as the data quality and model matured, there is a weak trend of decreasing AHR percentages across AHR2, AHR3, AHR5, AHR7, AHR10 and AHR12, with only AHR1, AHR4 and AHR9 showing an increasing trend.

IHACPA will continue to monitor the prevalence of AHRs in the general hospital episode data. For further insights based on 'real world' trends rather than modelling data, refer to the AHR section of the IHACPA National Benchmarking Portal.[8]

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[7] 2020–25 National Health Reform Agreement (NHRA)

[8] National Benchmarking Portal

Figure A1. Yearly readmission percentage of total records as a fraction of total national records since the creation of the AHR model.
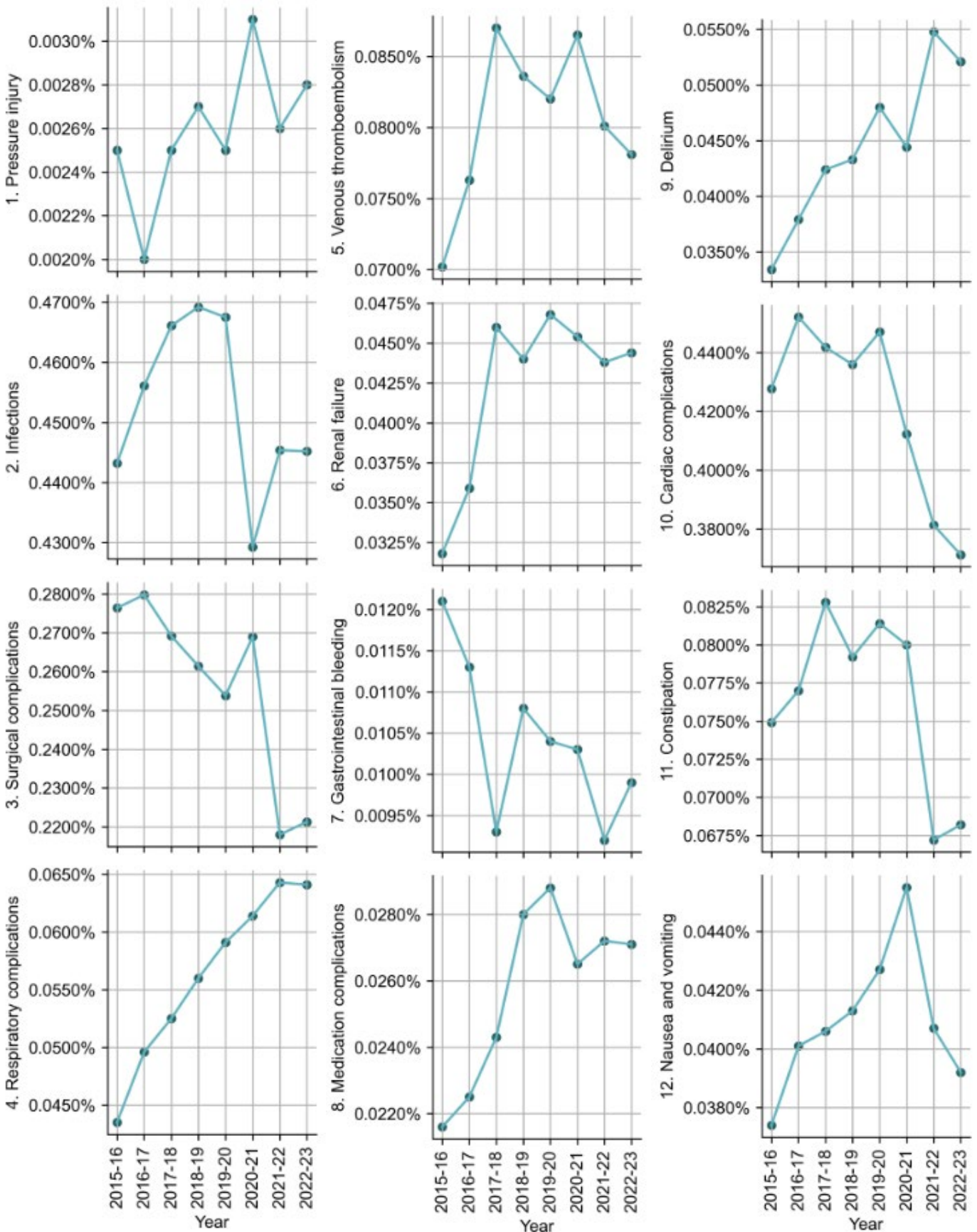
Appendix B: A brief context of AHR adjustment model development

Overview

From 1 July 2019, IHACPA commenced a 24-month shadow period encompassing three funding options for avoidable hospital readmissions:

- Option one: Deduct the cost of the readmission episode from the index episode;
- Option two: Combine the index and readmission episodes and recalculate the funding of the combined episode;
- Option three: Adjust funding at the hospital level where actual rates of avoidable readmissions exceed expected rates of avoidable readmissions.

Throughout the shadow period IHACPA worked closely with jurisdictional stakeholders in analysing and evaluating the three scope options for potential implementation.

The majority of stakeholders expressed a preference for funding option one throughout the shadow period. Funding option one is the simplest to apply as it follows the same methodology as the HACs adjustment, where the funding adjustment is applied to the index admission. Of the funding options investigated, option one impacted the jurisdictions more proportionately when compared to funding options two and three, which showed adjustment bias against smaller regional and remote hospitals when the scope is expanded beyond the hospital level.

Stakeholders initially had reservations about the potentially punitive effect of funding option one for episodes involving a transfer within hospital networks. IHACPA has made the decision to trim transfer episodes from the readmissions data to consolidate this risk and provide a more accurate picture of the readmissions landscape.

Stakeholders also expressed concerns about funding option one being a disincentive for hospitals to discharge patients to avoid penalisation for a potential readmission. However, this could be viewed as a positive change in clinical behaviour to reduce avoidable readmissions and improve patient safety if discharges were previously occurring too early.

Funding option for implementation

Following a development and consultation period, IHACPA implemented the funding adjustment for avoidable hospital readmissions using funding option one, i.e. deducting the cost of the readmission episode from the index episode.

Under this episode-level approach, an avoidable hospital readmission nominally receives no funding adjustment, with a funding adjustment applied to impact on where the index admission occurred (even when the readmission occurred in a different hospital/LHN to the index admission).

To accomplish this, an NWAU adjustment is applied to the index episode, based on the total NWAU of the associated readmission. For episodes considered low risk under the risk adjustment methodology, the full NWAU of the readmission episode is deducted from the index episode (up to the value of the index episode). This is similar to the full incremental cost deduction in the context of HACs.

This option is risk adjusted by the adjustment factors discussed above, for example, if the risk of a readmission is high, only a small percentage of the readmitted episode NWAU is deducted from the index episode.

Appendix C: Preliminary AHR risk adjustment modelling

Logistic regression – The original AHR model

The original modelling approach investigated for avoidable readmissions was based on the HACs logistic regression model. This modelling approach had limitations due to the large number of false positive outputs (where readmissions were identified for episodes where it had not occurred) from a much larger data set of non-readmission episodes. The logistic regression approach showed poor performance on episodes that were not readmissions and provided a less than optimal fit to the given data.

Receiver operating characteristic curves (ROC curves) were originally used to measure AHR model performance, however these presented an incomplete picture of model performance trained on imbalanced data. IHACPA has since updated the metrics used to describe the performance of the readmissions risk adjustment model to include areas under precision recall curves (PRC) as well, which gives a more complete idea of the performance of the model on highly unbalanced data.

The original logistic regression risk model estimated the effect of each risk factor independently. For example, for a given readmission category, being admitted to an intensive care unit (ICU) might indicate an increased risk of readmission of 3 per cent. Each risk factor had an associated marginal risk like this which, when added together, gave a total risk score. Due to poor performance, this method was replaced with one based on decision trees.

Figure C1 demonstrates an example of the historic PRC for readmission 10 when using the logistic regression model. Picking a threshold which identifies 20% of unplanned readmissions (recall) in the data set, the model has a precision of around 8%, meaning that it will return about 28,000 episodes correctly classified as leading to an avoidable hospital readmission, and around 130,000 false positives.

Figure C1: Precision Recall curve for readmission 10 with logistic regression model
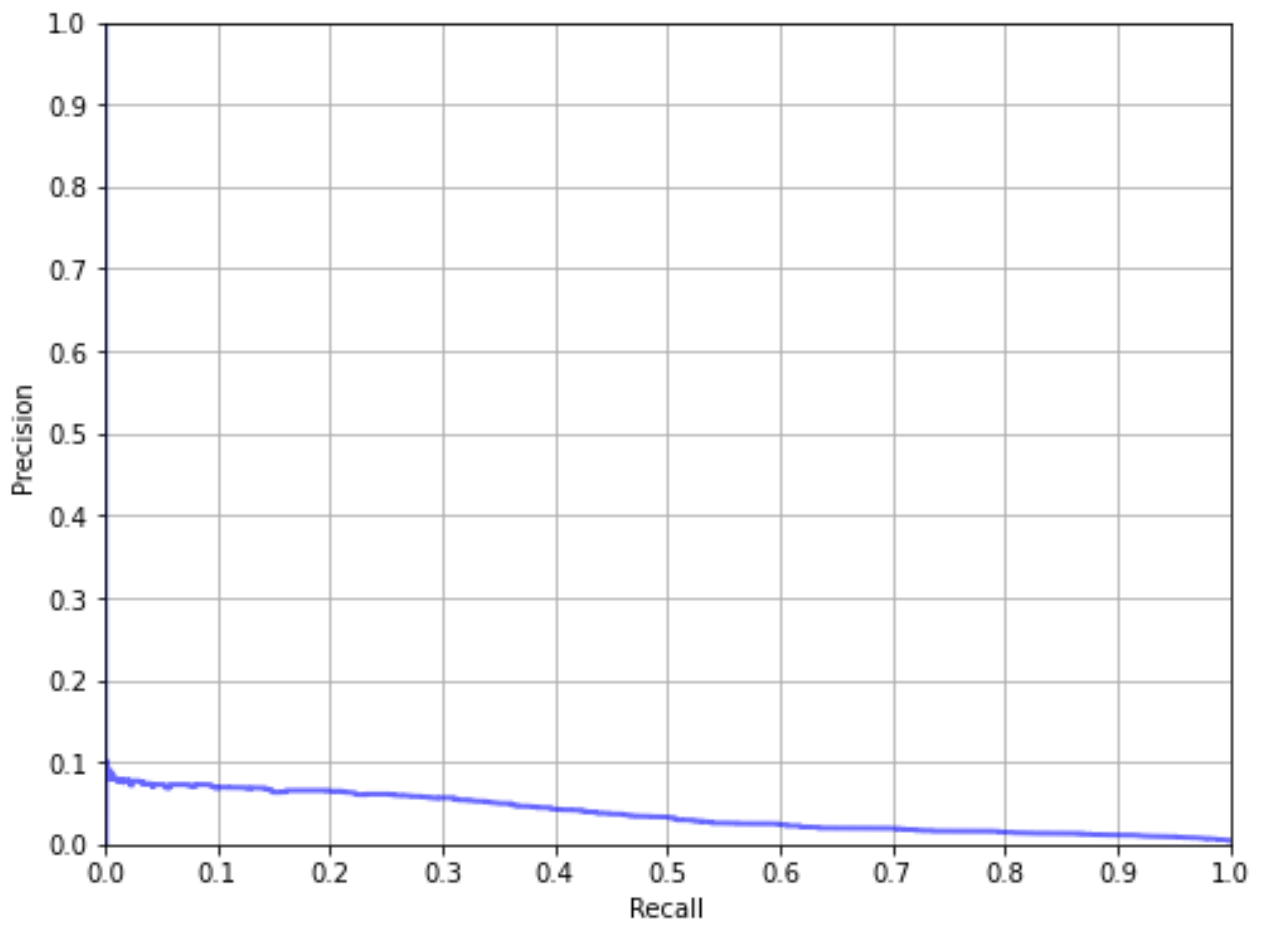
Decision trees – The first AHR model improvement

IHACPA investigated the performance of regression-based decision tree models as an alternative to the logistic regression model used for HACs. The model built a decision tree to classify the target variable by selecting features that give the highest information gain and splitting the data set on that feature. Figure C2 shows an example of a regression-based decision tree model for the Cardiac complications readmission category. Decision trees are easily visualised and understood, but have a large risk of overfitting or failing to generalize beyond training data with large, complex models.

Figure C2: Example regression based decision tree classifier for Readmission 10 – Cardiac complications
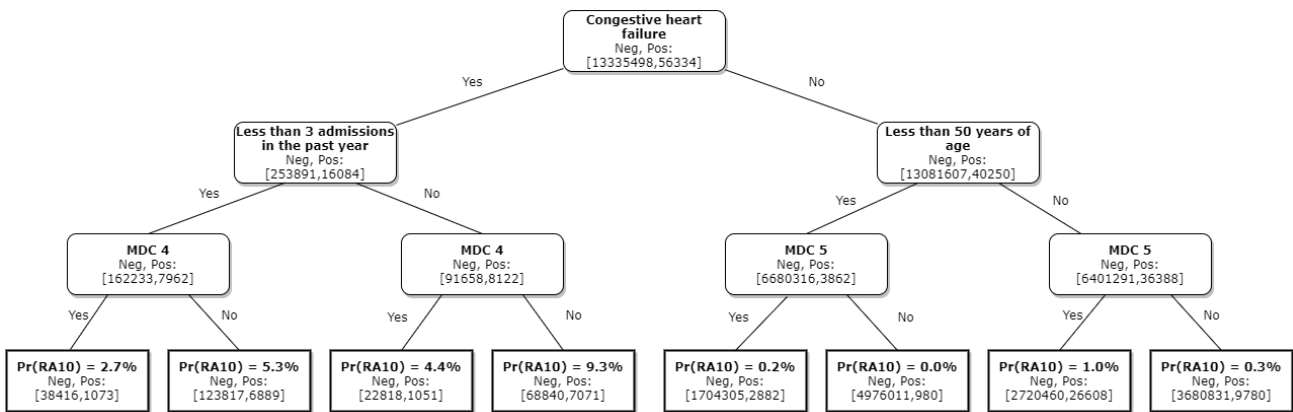
In Figure C2, the numbers in square brackets show how many non-readmissions (Neg) and readmissions (Pos) are considered at each stage. These episodes are then split on the risk factor (stated in bold) and shown on the next level of the decision tree.

For example, the node at the top of the tree shows that 13,335,498 non-readmissions and 56,334 cardiac complication readmissions are considered in this model. These are then split, based on whether the episode has the congestive heart failure risk factor, into 253,891 non-readmissions and 16,084 cardiac complication readmissions with congestive heart failure, and 13,081,607 non-readmissions and 40,250 cardiac complication readmissions without congestive heart failure.

Splitting on the congestive heart failure risk factor produces two nodes where less than 2 per cent of non-readmissions are on the left-hand side, though it contains over 28 per cent of cardiac complication readmissions. We therefore say that splitting on this feature produces a high information gain. This process is repeated, splitting on episodes with less than 3 admissions in the past year, then again on the major diagnostic category (MDC) risk factor, specifically if the episode is in MDC 4. At each level of the decision tree, the model identifies the risk factor that produces the highest information gain and splits the data set on this.

Leaf nodes are produced at the bottom of the chart. If the model was allowed to continue splitting the data set until each leaf node was either purely non-readmissions or purely readmissions, it would produce a much deeper model than is shown in Figure C2, with many more layers of nodes. To avoid overfitting, however, the model was limited to a "depth" of five layers of nodes (three in the example tree shown). The leaf nodes at the bottom of Figure C2, therefore; output the probability of whether an episode with the corresponding risk factors will lead to an avoidable readmission for cardiac complications.

Tracing a single example through the model in Figure C2, if an episode: has the congestive heart failure risk factor; more than three admissions in the previous year; and is not in MDC 4, the model says that this episode has a 9.3% chance of leading to an avoidable readmission for a cardiac complication.

To combat the overfitting and general poor fit of decision trees on the AHR datasets, GBDT methods were adopted for the AHR model. Refer to Section 5.2 for more details.

Appendix D: Selection of and reassessment of risk factors

The AHR risk adjustment model consists of a series of GBDT models, one for each AHR. Each model assigns episodes a complexity value, based on their unique risk flags. Due to the machine learning nature of the model, risk factors interact in complex, interrelated manners to form the final complexity output.

IHACPA has established a general process for assessing risk factors included in the risk adjustment model. The process involves:

a) (For new risk factors) A preliminary assessment to determine whether there is adequate volume of information to allow for their use.

b) Assessing the relative feature performance of the risk factor in predicting the occurrence of a AHR across 3 years and

c) Seeking clinical advice on the appropriateness of the proposed risk factor.

Testing risk factor significance

Feature importance plots provide information on the risk factors used in the AHR model. During the shadow period, the top performing risk factors with the largest contribution to predicting the readmission category were used in the AHR-level risk adjustment models, based on a minimum relative feature importance threshold of 0.01. This approach was selected as it does not trim potentially important risk factors in some readmission categories, as would be the case if limited to an arbitrary number of risk factors (for example, top 10 risk factors), and as it removes risk factors that are not statistically significant for other readmission categories from consideration in those models.

This process allows for re-evaluation of risk factors in AHRs, with the additional criteria that a risk factor must be considered significant for two of the past three years before it is considered for implementation. Risk factor reevaluation is carried out through creating GBDT models for each AHR group, using every risk factor. This allows for the identification of risk factors for addition or removal, when considered across three NEP years.

Overall, this approach reflects the best risk factors (of those considered) for the best performing risk adjustment model for each readmission category. However, this method does have some

shortcomings in that the models for certain readmission categories may perform less optimally than other categories due to low episode sample sizes. This is particularly true for the pressure injury and gastrointestinal bleeding categories, where the extremely low sample sizes means that both risk factor selection and the risk model in general are less robust compared to the other readmission categories.

Another consideration is the use of chronic condition flags as risk factors, due to concerns that if the presence of a chronic condition impacts the course of care, it would be coded differently. The primary purpose of using Charlson comorbidity flags and chronic condition flags is to capture whether a patient has these types of conditions, and their related risk of readmission. For example, if a patient was readmitted for renal failure, their risk profile would be affected by having one or more of the chronic condition flags and they are therefore more likely to be readmitted due to their chronic condition.

Seeking clinical advice

IHACPA will seek the advice of the CAC on the selection, addition and removal of risk factors in the AHR risk adjustment model. This will generally be undertaken in two stages, firstly to propose risk factors for broad consideration and exploration and then subsequently, after statistical analysis, seek advice on any finalised updates to the risk model.

IHACPA has previously received advice querying the use of length of stay in the risk adjustment model, as it is a factor under the control of the hospital and influenced by processes of care. There was concern that it could potentially capture patients who were discharged too early or be indicative of a less complex patient. While length of stay is not used as a risk factor in the AHR model, low length of stay flag is used as a risk factor. Additionally, based on feedback during development of the AHR model, readmissions where the index admission has a separation mode of discharged against medical advice are excluded from adjustment.

Historical advice

Historical advice was obtained through consultation with clinical and jurisdictional committees during the shadow period, and through consultation with the University of Melbourne. Advice is separated into general feedback, summarised below at the document or committee level, and advice on specific treatment of AHR risk factors (Table D1).

Feedback from the University of Melbourne

IHACPA consulted with the University of Melbourne on the creation of the AHR model. During this time, the University of Melbourne provided advice at both a general and risk factor level. General advice included to:

- Retain a core set of risk factors for all models regardless of statistical significance, based on consultation and clinical feedback
- Use statistical methods to determine the validity of AHR level risk factors for inclusion outside this core set and supplement this statistical criteria with clinical and policy considerations
- Consider the removal of AHRs that do not show enough records for the development of a stable model from the modelling process

- Not use risk factors that are more granular or which flag less than 5% of the total modelling dataset
- Use individual Charlson score components as flags, rather than as an aggregate Charlson score to allow for greater granularity.

Feedback to the Consultation paper on the pricing framework for Australian public hospital services 2021-22

General feedback to this consultation paper included:

- Queensland Health raised concerns that the inclusion of Indigenous status as a risk adjustment variable, in spite of being significant to readmissions, may give the perception of acceptance that nothing can/should be done to work with Indigenous groups to prevent readmissions. They also raised concern that the inclusion of number of readmissions in the previous years, while a potential indicator of how sick a patient is, may also reflect establishment admission policies and practices.
- Children's Health Queensland Hospital and Health Service supported the inclusion of young age specific flagging. This was resolved with the decision to exclude neonatal episodes from AHR adjustment based on the specification from the Commission. It also advised that episodes with an index episode having a discharge mode that indicated discharge against medical advice should be excluded from risk adjustment. This was eventually incorporated into the Commission Technical Specification.
- The WA department of Health and Women's and Children's Healthcare Australia both supported the inclusion of paediatric specific risk factors in AHR modelling. This was resolved with the decision to exclude neonatal episodes from AHR adjustment based on the specification from the Commission.
- Women's and Children's Healthcare Australia recommended the exclusion of episodes with discharge modes that indicated discharge against medical advice. This is now part of the Commission Technical Specification. Similarly, there was a recommendation of paediatric specific risk factors, which are no longer relevant to the adopted model due to exclusion of neonatal episodes from risk adjustment.

CAC Feedback

Feedback from IHACPA's CAC during development of the AHR model indicated that:

- Paediatric risk factors were not planned for inclusion due to the exclusion of neonatal episodes from AHR modelling.
- CAC advice raised no concerns on the clinical relevance of the final risk factors chosen by IHACPA for AHR modelling, which were based on the top performing risk factors from relative feature importance and reached consensus to support IHACPA's proposed risk adjustment model based on funding option 1.

AHR Reports

There were four AHR Reports produced during the development of the AHR model. These reports built on the information presented in each other, taking a similar form to the AHR Technical Specifications by the final report. The AHR Reports provided updates on action on the advice received throughout the AHR model development period, and indicated that:

- Feature importance tables were chosen and reported as a method of validating the significance of proposed risk factors, and demonstrated that admissions in the previous year were a significant risk factor for all reasonably large sample size risk factors. This is in keeping with advice from the University of Melbourne included in Table D1.

Further advice was largely based on feedback from the University of Melbourne.

Table D1: Historical advice relating to the use of specific risk factors

Source	Risk Factor Advice
The University of Melbourne	- Use annual volume and rurality as potential risk factors instead of peer group. - Use long stay and short stay outlier flags for testing instead of length of stay, which is a contentious variable in the literature - It is recommended to include the number of procedures in the index admission - It is recommended to include number of admissions in the previous year - Use individual Charlson score component flags instead of an aggregate Charlson score - It is highly recommended to include socioeconomic status as a risk factor The University of Melbourne additionally recommended setting a set of core risk factors that are clinically important, so included regardless of statistical importance, and excluding or changing the bagging of risk factors that are granular enough to flag less than 5% of the sample.
Queensland Health	- Cautions against inclusion of Indigenous status as, while significant, it may represent a decision to risk adjust away, not highlight, the decreased health outcomes of Indigenous people - Cautions against the use of number of readmissions in the past year
NSW Health	Advises the use of an expanded set of risk factors in AHRs compared to HACs, including a range of diabetes and malignant conditions
Children's Health Queensland Hospital and Health Services	- Charlson comorbidity flags should be used as risk factors to identify high risk patients - Age and weight should be included as a risk factor. This was provided in the context of neonatal patients, which are currently excluded from risk adjustment, but age group is considered. - Use chronic conditions flags to identify malignancy, cystic fibrosis, inflammatory bowel disease, immunocompromised patients and haemophilia patients, and use these flags as risk factors
Victorian Department of Health and Human Services	- Use socio-economic factors as risk factors - Recommends the inclusion of non-English speaking background as a risk factor

Western Australia Department of Health	• Use remoteness and rurality as potential risk factors
	• Use socio-demographic factors, including accommodation status, cultural status and refugee status as risk factors
	• Consider separating advanced neoplastic disease and oesophageal cancers from other similar conditions, since they may behave differently
	• Paediatric risk factors, including Rhee score, should be considered. This is not considered in the existing model, since neonatal episodes are excluded.
Women's and Children's Healthcare Australia	• Recommends the inclusion of paediatric specific risk factors. This is not considered in the existing model since neonatal episodes are excluded.
CAC paper inclusions	Selection was based largely on relative feature importance during the shadow period:
	• IHACPA sought advice on if the following risk factors should be included for all AHRs regardless of statistical performance:
	o Age
	o Major diagnostic category (MDC)
	o Emergency status and
	o DRG type
	• No feedback was noted to support or contradict this selection
	• IHACPA sought any information of further suggested risk factors to include regardless of statistical significance, with no further suggestions noted
	• IHACPA suggested the trimming of ICU hours, mental health flag, presence of a pacemaker, dependence on ventilation, post transplant status, asthma status and presence of a HAC from the AHR risk factors based on relative feature importance
AHR reports (Report One to Four)	• Number of admissions in the past year proved significant for the majority of risk factors, and is strongly recommended for inclusion in each AHR group
	• Length of stay in the index admission, which was used in report 1-3, should be revised to short stay outlier flag based on balancing a need to capture patients who were discharged too early against stakeholder influence on care
	• Long stay outlier flag was not considered
	• Socio-economic Indexes for Areas (SEIFA) is a capturable proxy for socioeconomic status. The AHR Second Report noted it to not be a strong predictor, so removed it from subsequent testing.

Other general considerations

Advice on risk flagging should be followed when possible using the available activity datasets. Any changes to the risk factors in the AHR risk adjustment model should seek to optimise the statistical model performance and reflect model clinical considerations.

Appendix E: Shadow period risk factors, Charlson diagnosis codes and chronic condition diagnosis codes

Table E1: Risk factors assessed throughout the shadow period

First Report	Second Report	Third Report
• Patient age • Gender • Indigenous status • Treatment remoteness • Diagnosis related group type (medical, surgical, other) • MDC • Charlson score • Socio-Economic Indexes for Areas (SEIFA) • ICU status • Admission status • Transfer status	• Patient age • Charlson score • MDC • Emergency status • ICU hours • AR-DRG type • Gender • Transfer status • Patient remoteness • Indigenous status • Mental health condition present • Presence of a pacemaker • Dependence on ventilation • Post transplant • Asthma • Obesity/malnutrition • Presence of a HAC	• Patient age • MDC • Emergency status • ICU hours • AR-DRG type • Gender • Transfer status • Patient remoteness • Indigenous status • Mental health condition present • Presence of a pacemaker • Dependence on ventilation • Post transplant • Asthma • Obesity • Malnutrition • Presence of a HAC • Length of stay in the index admission • Number of procedures undergone in the index admission • Number of hospital admissions in the year prior to the index admission • Charlson comorbidity diagnostic categories • Chronic condition flags

Table E2: Previous Charlson diagnostic category definitions – Used up to NEP23

Diagnostic category	Diagnosis Codes
Acute myocardial infarction	I21-prefix I22-prefix I25.2-prefix
Congestive heart failure	I50-prefix
Peripheral vascular disease	I71-prefix I79.0-prefix I73.9-prefix R02-prefix Z95.8-prefix Z95.9-prefix
Cerebral vascular accident	I60-prefix I61-prefix I62-prefix I63-prefix I65-prefix I66-prefix G45.0-prefix G45.1-prefix G45.2-prefix G45.8-prefix G45.9-prefix G46-prefix I64-prefix G45.4-prefix I67.0-prefix I67.1-prefix I67.2-prefix I67.4-prefix I67.5-prefix I67.6-prefix I67.7-prefix I67.8-prefix I67.9-prefix I68.1-prefix I68.2-prefix I68.8 I-prefix 69-prefix
Dementia	F00-prefix F01-prefix F02-prefix F05.1-prefix
Pulmonary disease	J40-prefix J41-prefix J42-prefix J44-prefix J43-prefix J45-prefix J46-prefix J47-prefix J67-prefix J60-prefix J61-prefix J62-prefix J63-prefix J66-prefix J64-prefix J65-prefix
Connective tissue disorder	M32-prefix M34-prefix M33.2-prefix M05.3-prefix M05.8-prefix M05.9-prefix M06.0-prefix M06.3-prefix M06.9-prefix M05.0-prefix M05.2-prefix M05.1-prefix M35.3-prefix
Peptic ulcer	K25-prefix K26-prefix K27-prefix K28-prefix
Liver disease	K70.2-prefix K70.3-prefix K73-prefix K71.7-prefix K74.0-prefix K74.2-prefix K74.6-prefix K74.3-prefix K74.4-prefix K74.5-prefix
Diabetes	E10.9-prefix E11.9-prefix E13.9-prefix E14.9-prefix E10.1-prefix E11.1-prefix E13.1-prefix E14.1-prefix E10.5-prefix E11.5-prefix E13.5-prefix E14.5-prefix
Diabetes complications	E10.2-prefix E11.2-prefix E13.2-prefix E14.2-prefix E10.3-prefix E11.3-prefix E13.3-prefix E14.3-prefix E10.4-prefix E11.4-prefix E13.4-prefix E14.4-prefix
Paraplegia	G81-prefix G04.1-prefix G82.0-prefix G82.1-prefix G82.2-prefix
Renal disease	N03-prefix N05.2-prefix N05.3-prefix N05.4-prefix N05.5-prefix N05.6-prefix N07.2-prefix N07.3-prefix N07.4-prefix N01-prefix N18-prefix N19-prefix N25-prefix
Cancer	C0-prefix C1-prefix C2-prefix C3-prefix C40-prefix C41-prefix C43-prefix C45-prefix C46-prefix C47-prefix C48-prefix C49-prefix C5-prefix C6-prefix C70-prefix C71-prefix C72-prefix C73-prefix C74-prefix C75-prefix C76-prefix C80-prefix C81-prefix C82-prefix C83-prefix C84-prefix C85-prefix C88.3-prefix C88.7-prefix C88.9-prefix C90.0-prefix C90.1-prefix C91-prefix C92-prefix C93-prefix C94.0-prefix C94.1-prefix C94.2-prefix C94.3-prefix C94.5-prefix C94.7-prefix C95-prefix C96-prefix
Metastatic cancer	C77-prefix C78-prefix C79-prefix
Severe liver disease	K72.9-prefix K76.6-prefix K76.7-prefix K72.1-prefix
HIV	B20-prefix B21-prefix B22-prefix B23-prefix B24-prefix

Table E3: Chronic disease code categories

Chronic category	U code	Chronic condition codes
Obesity	U78.1	E66.9 (ICD-10-AM 10th edition only) E66.90 E66.91 E66.92 E66.93 (ICD-10-AM 11th and 12th edition only)
Cystic fibrosis	U78.2	E84
Dementia	U79.1	F03 F00.0 F00.1 F00.2 F00.9 F01.0 F01.1 F01.2 F01.3 F01.8 F01.9 F02.0 F02.1 F02.2 F02.3 F02.4 F02.8 (ICD-10-AM 10th and 11th edition only) F00.00 F00.01 F00.10 F00.11 F00.20 F00.21 F00.90 F00.91 F01.00 F01.01 F01.10 F01.11 F01.20 F01.21 F01.30 F01.31 F01.80 F01.81 F01.90 F01.91 F02.00 F02.01 F02.10 F02.11 F02.20 F02.21 F02.30 F02.31 F02.40 F02.41 F02.80 F02.81 F03.00 F03.01 (ICD-10-AM 12th edition only)
Schizophrenia	U79.2	F20.0 F20.1 F20.2 F20.3 F20.4 F20.5 F20.6 F20.8 F20.9
Depression	U79.3	F33.4 F33.8 F33.9 F32.00 F32.01 F32.10 F32.11 F32.20 F32.21 F32.30 F32.31 F32.80 F32.81 F32.90 F32.91
Disorder of intellectual development	U79.4	F70.0 F70.1 F70.8 F70.9 F71.0 F71.1 F71.8 F71.9 F72.0 F72.1 F72.8 F72.9 F73.0 F73.1 F73.8 F73.9 F78.0 F78.1 F78.8 F78.9 F79.0 F79.1 F79.8 F79.9
Parkinson's disease	U80.1	G20
Multiple sclerosis	U80.2	G35
Epilepsy	U80.3	G40.00 G40.01 G40.10 G40.11 G40.20 G40.21 G40.30 G40.31 G40.40 G40.41 G40.50 G40.51 G40.60 G40.61 G40.70 G40.71 G40.80 G40.81 G40.90 G40.91
Cerebral palsy	U80.4	G80.9 G80.00 G80.01 G80.02 G80.03 G80.09
Tetraplegia, paraplegia, diplegia, monoplegia and hemiplegia, due to any cause	U80.5	G81.0 G81.1 G81.9 G83.0 G83.1 G83.2 G83.3 G82.00 G82.02 G82.04 G82.06 G82.10 G82.12 G82.14 G82.16 G82.20 G82.22 G82.24 G82.26 G82.30 G82.32 G82.34 G82.36 G82.40 G82.42 G82.44 G82.46 G82.50 G82.52 G82.54 G82.56
Ischaemic heart disease	U82.1	I25.9 I25.10 I25.11 I25.12 I25.13
Chronic heart failure	U82.2	I50.0 I50.9
Hypertension	U82.3	I10
Emphysema without mention of COPD	U83.1	J43.9
Chronic obstructive pulmonary disease	U83.2	J44.9
Asthma, without mention of COPD	U83.3	J45.0 J45.1 J45.8 J45.9

Bronchiectasis without mention of CF	U83.4	J47
Chronic respiratory failure	U83.5	J96.10 J96.11 J96.19
Crohn's disease	U84.1	K50.9 K50.8 K50.1 K50.0
Ulcerative colitis	U84.2	K51.0 K51.2 K51.3 K51.8 K51.9
Chronic liver failure	U84.3	K72.1
Rheumatoid arthritis	U86.1	M06.90 M06.91 M06.92 M06.93 M06.94 M06.95 M06.96 M06.97 M06.98 M06.99
Arthritis and osteoarthritis	U86.2	M15.0 M16.0 M16.1 M17.0 M17.1 M18.0 M18.1 M13.90 M13.91 M13.92 M13.93 M13.94 M13.95 M13.96 M13.97 M13.98 M13.99 M19.01 M19.02 M19.03 M19.04 M19.07 M19.08 M19.09 M47.90 M47.91 M47.92 M47.93 M47.94 M47.95 M47.96 M47.97 M47.98 M47.99
Systemic lupus erythematosus	U86.3	M32.0 M32.1 M32.8 M32.9
Osteoporosis	U86.4	M81.90 M81.91 M81.92 M81.93 M81.94 M81.95 M81.96 M81.97 M81.98 M81.99
Chronic kidney disease stage 3 to 5	U87.1	N18.3 N18.4 N18.5
Spina bifida	U88.1	Q05.00 Q05.01 Q05.02 Q05.10 Q05.11 Q05.12 Q05.20 Q05.21 Q05.22 Q05.30 Q05.31 Q05.32 Q05.40 Q05.41 Q05.42 Q05.50 Q05.51 Q05.52 Q05.60 Q05.61 Q05.62 Q05.70 Q05.71 Q05.72 Q05.80 Q05.81 Q05.82 Q05.90 Q05.91 Q05.92
Down's syndrome	U88.2	Q90.0 Q90.1 Q90.2 Q90.9

Appendix F: Risk factor definitions

Risk factor group	Diagnostic category	Diagnosis Codes
Standalone categories	Mental health	F-prefix R45.81 U79-prefix
	Drug use	F10-prefix to F19-prefix Z64.2-prefix Z72.2-prefix
	Homelessness	Z59.0-prefix
	Post transplant status	Z94-prefix
	Pacemaker status	Z95.0
	Ventilator	Z99.1
	Asthma	J45-prefix J46-prefix U83.3
	Obesity	E66.90 E66.91 E66.92 E66.93 E66.1-prefix E66.2-prefix
	Malnutrition	E40 E41 E42 E43 E44.0 E44.1 E45 E46
	Parkinson disease	G21-prefix G22-prefix
	Dystocia	P03.1 O66.0
Charlson Categories	Acute myocardial infarction	I21-prefix I22-prefix
	Congestive heart failure	I50-prefix I11.0-prefix I13.0-prefix I13.2-prefix U82.2
	Peripheral vascular disease	I70-prefix I71-prefix I73-prefix
	Cerebral vascular accident	I60-prefix to I66-prefix I67.0-prefix to I67.9-prefix I68.0-prefix to I68.2-prefix I68.8-prefix I69-prefix
	Dementia	F00-prefix F01-prefix F03-prefix U79.1-prefix
	Pulmonary disease	J40-prefix to J47-prefix J60-prefix to J67-prefix U83.1 U83.2 U83.3 U83.4
	Connective tissue disorder	M30-prefix to M36-prefix M05-prefix M06-prefix U86.1 U86.3

Risk factor group	Diagnostic category	Diagnosis Codes
	Peptic ulcer	K25-prefix to K28-prefix
	Liver disease	K70.0-prefix to K70.3-prefix K70.9-prefix K71.0-prefix K71.2-prefix to K71.9-prefix K72.0-prefix K73-prefix to K75-prefix K76.0-prefix to K76.4-prefix K76.8-prefix K76.9-prefix B18-prefix
	Diabetes	E10.8 E10.9 E11.8 E11.9 E13.8 E13.9 E14.8 E14.9-prefix
	Diabetes complications	E10.0-prefix to E10.7-prefix E11.0-prefix to E11.7-prefix E13.0-prefix to E13.7-prefix E14.0-prefix to E14.7-prefix
	Paraplegia	G81-prefix G82.0-prefix to G82.2-prefix
	Renal disease	N03-prefix N05.2-prefix to N05.6-prefix N07.2-prefix to N07.4-prefix N01-prefix N18.3-prefix to N18.5-prefix N18.9-prefix N19-prefix N25-prefix I12.0-prefix I13.1-prefix Z49.0-prefix to Z49.2-prefix U87.1
	Cancer	C0-prefix to C3-prefix C40-prefix C41-prefix C43-prefix C45-prefix to C49-prefix C5-prefix C6-prefix C70-prefix to C76-prefix C80-prefix to C86-prefix C88.0-prefix C88.2-prefix to C88.4-prefix C88.7-prefix C88.9-prefix C90.0-prefix to C90.3-prefix C91.1-prefix C91.3-prefix to C91.9-prefix C92-prefix C93.0-prefix C93.1-prefix C93.3-prefix C93.7-prefix C93.9-prefix C94.0-prefix C94.2-prefix to C94.4-prefix C94.6-prefix C94.7-prefix C95.0-prefix C95.1-prefix C95.7-prefix C95.9-prefix D46-prefix D45
	Metastatic cancer	C77-prefix to C79-prefix
	Severe liver disease	K70.4-prefix K71.1-prefix K72.1-prefix K72.9-prefix K76.5-prefix to K76.7-prefix Z94.4-prefix U84.3
	HIV	B20-prefix to B24-prefix R75-prefix Z21-prefix

Table F2. ICD-10-AM 12th edition codes used for flagging chronic conditions for AHR modelling

Chronic category	U code	Chronic condition codes
Obesity	U78.1	E66.9 (ICD-10-AM 10th edition only) E66.90 E66.91 E66.92 E66.93 (ICD-10-AM 11th and 12th edition only)
Cystic fibrosis	U78.2	E84
Dementia	U79.1	F03 F00.0 F00.1 F00.2 F00.9 F01.0 F01.1 F01.2 F01.3 F01.8 F01.9 F02.0 F02.1 F02.2 F02.3 F02.4 F02.8 (ICD-10-AM 10th and 11th edition only) F00.00 F00.01 F00.10 F00.11 F00.20 F00.21 F00.90 F00.91 F01.00 F01.01 F01.10 F01.11 F01.20 F01.21 F01.30 F01.31 F01.80 F01.81 F01.90 F01.91 F02.00 F02.01 F02.10 F02.11 F02.20

Chronic category	U code	Chronic condition codes
		F02.21 F02.30 F02.31 F02.40 F02.41 F02.80 F02.81 F03.00 F03.01 (ICD-10-AM 12th edition only)
Schizophrenia	U79.2	F20.0 F20.1 F20.2 F20.3 F20.4 F20.5 F20.6 F20.8 F20.9
Depression	U79.3	F33.4 F33.8 F33.9 F32.00 F32.01 F32.10 F32.11 F32.20 F32.21 F32.30 F32.31 F32.80 F32.81 F32.90 F32.91
Disorder of intellectual development	U79.4	F70.0 F70.1 F70.8 F70.9 F71.0 F71.1 F71.8 F71.9 F72.0 F72.1 F72.8 F72.9 F73.0 F73.1 F73.8 F73.9 F78.0 F78.1 F78.8 F78.9 F79.0 F79.1 F79.8 F79.9
Parkinson's disease	U80.1	G20
Multiple sclerosis	U80.2	G35
Epilepsy	U80.3	G40.00 G40.01 G40.10 G40.11 G40.20 G40.21 G40.30 G40.31 G40.40 G40.41 G40.50 G40.51 G40.60 G40.61 G40.70 G40.71 G40.80 G40.81 G40.90 G40.91
Cerebral palsy	U80.4	G80.9 G80.00 G80.01 G80.02 G80.03 G80.09
Tetraplegia, paraplegia, diplegia, monoplegia and hemiplegia, due to any cause	U80.5	G81.0 G81.1 G81.9 G83.0 G83.1 G83.2 G83.3 G82.00 G82.02 G82.04 G82.06 G82.10 G82.12 G82.14 G82.16 G82.20 G82.22 G82.24 G82.26 G82.30 G82.32 G82.34 G82.36 G82.40 G82.42 G82.44 G82.46 G82.50 G82.52 G82.54 G82.56
Ischaemic heart disease	U82.1	I25.9 I25.10 I25.11 I25.12 I25.13
Chronic heart failure	U82.2	I50.0 I50.9
Hypertension	U82.3	I10
Emphysema without mention of COPD	U83.1	J43.9
Chronic obstructive pulmonary disease	U83.2	J44.9
Asthma, without mention of COPD	U83.3	J45.0 J45.1 J45.8 J45.9
Bronchiectasis without mention of CF	U83.4	J47
Chronic respiratory failure	U83.5	J96.10 J96.11 J96.19
Crohn's disease	U84.1	K50.9 K50.8 K50.1 K50.0
Ulcerative colitis	U84.2	K51.0 K51.2 K51.3 K51.8 K51.9
Chronic liver failure	U84.3	K72.1
Rheumatoid arthritis	U86.1	M06.90 M06.91 M06.92 M06.93 M06.94 M06.95 M06.96 M06.97 M06.98 M06.99

Chronic category	U code	Chronic condition codes
Arthritis and osteoarthritis	U86.2	M15.0 M16.0 M16.1 M17.0 M17.1 M18.0 M18.1 M13.90 M13.91 M13.92 M13.93 M13.94 M13.95 M13.96 M13.97 M13.98 M13.99 M19.01 M19.02 M19.03 M19.04 M19.07 M19.08 M19.09 M47.90 M47.91 M47.92 M47.93 M47.94 M47.95 M47.96 M47.97 M47.98 M47.99
Systemic lupus erythematosus	U86.3	M32.0 M32.1 M32.8 M32.9
Osteoporosis	U86.4	M81.90 M81.91 M81.92 M81.93 M81.94 M81.95 M81.96 M81.97 M81.98 M81.99
Chronic kidney disease stage 3 to 5	U87.1	N18.3 N18.4 N18.5
Spina bifida	U88.1	Q05.00 Q05.01 Q05.02 Q05.10 Q05.11 Q05.12 Q05.20 Q05.21 Q05.22 Q05.30 Q05.31 Q05.32 Q05.40 Q05.41 Q05.42 Q05.50 Q05.51 Q05.52 Q05.60 Q05.61 Q05.62 Q05.70 Q05.71 Q05.72 Q05.80 Q05.81 Q05.82 Q05.90 Q05.91 Q05.92
Down's syndrome	U88.2	Q90.0 Q90.1 Q90.2 Q90.9

Appendix G: Key risk factor breakdowns[9]

AHR1 - Pressure injury
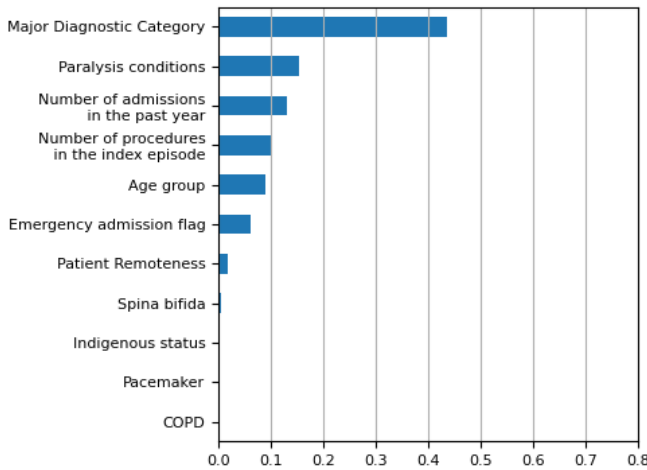
AHR2 - Infections
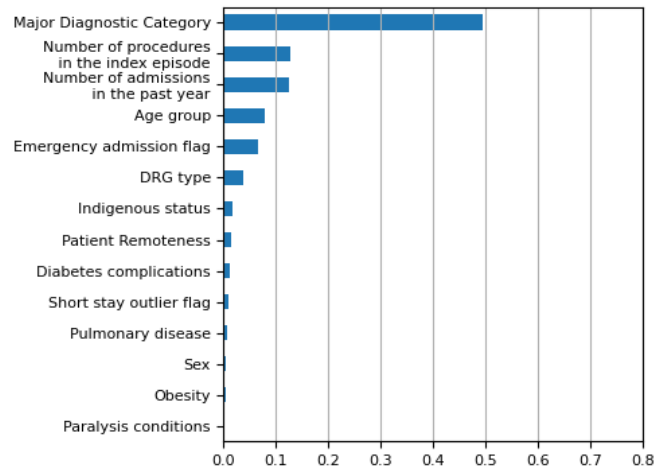
AHR3 - Surgical complications
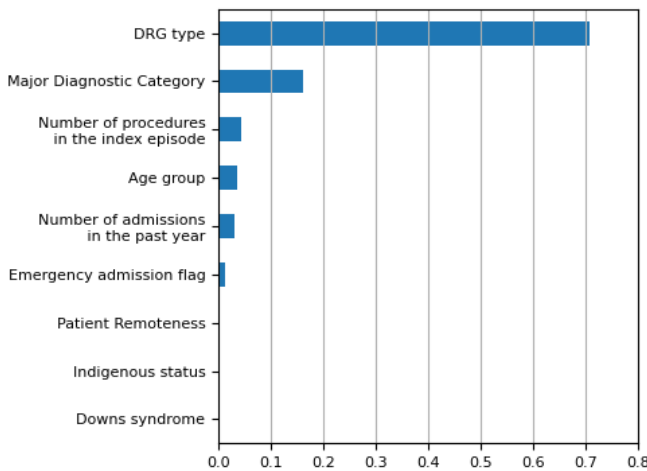
AHR4 - Respiratory complications
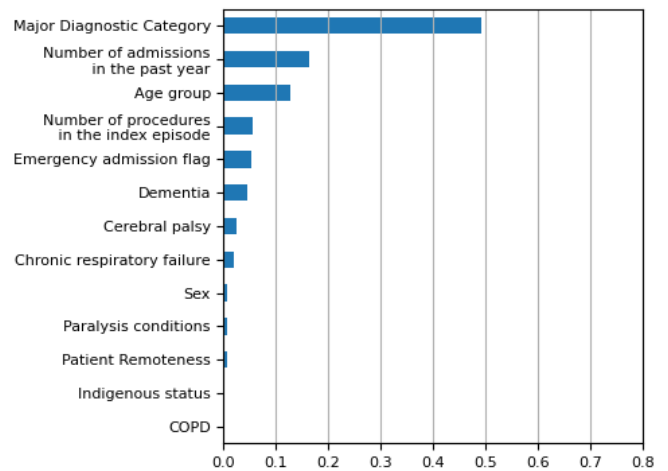
AHR5 - Venous thromboembolism
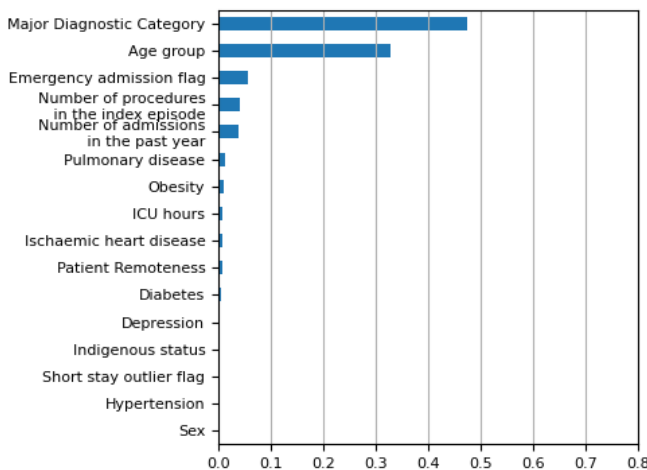
AHR6 - Renal failure
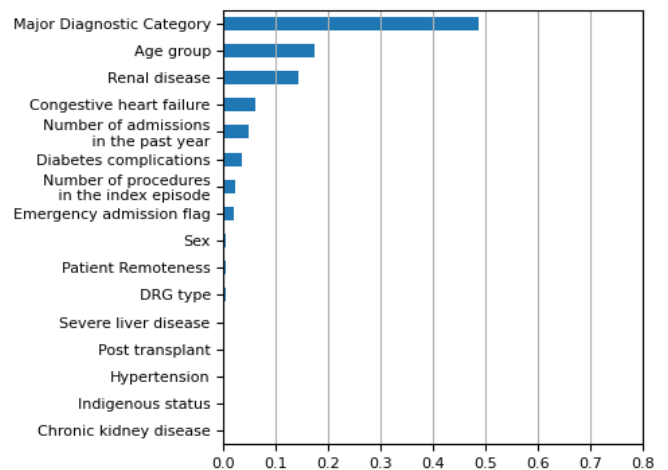
AHR7 - Gastrointestinal bleeding
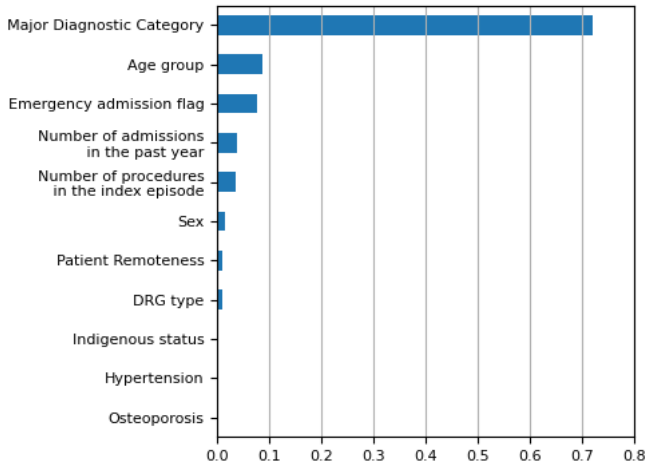
AHR8 - Medication complications
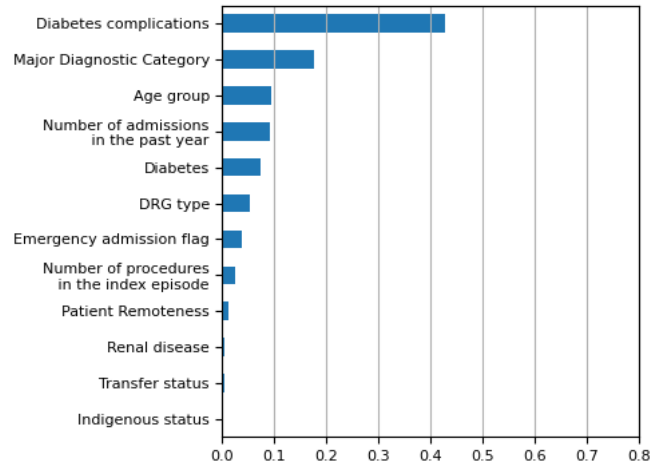
AHR9 - Delirium
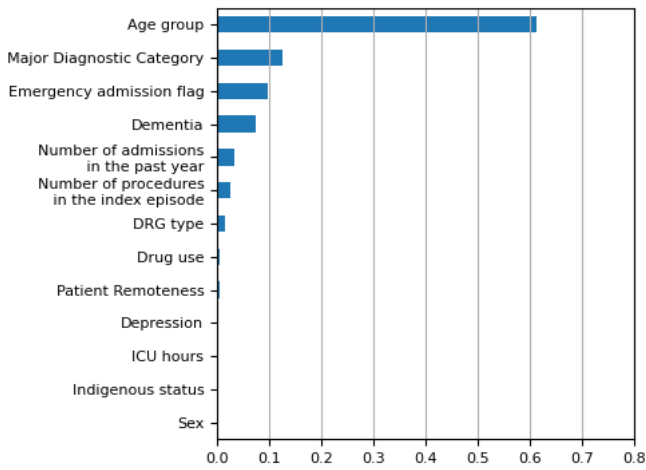
AHR10 - Cardiac complications
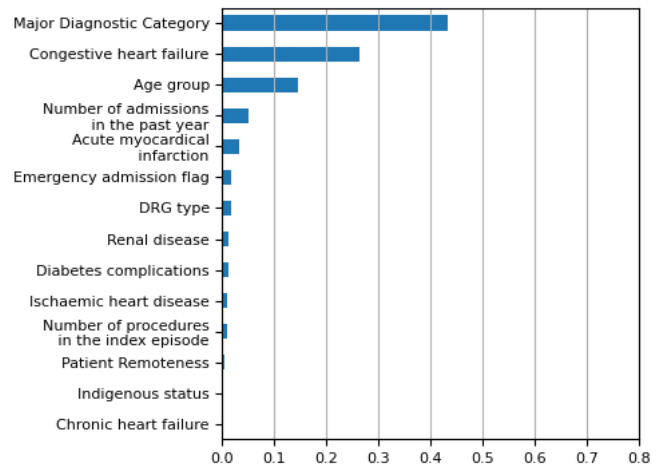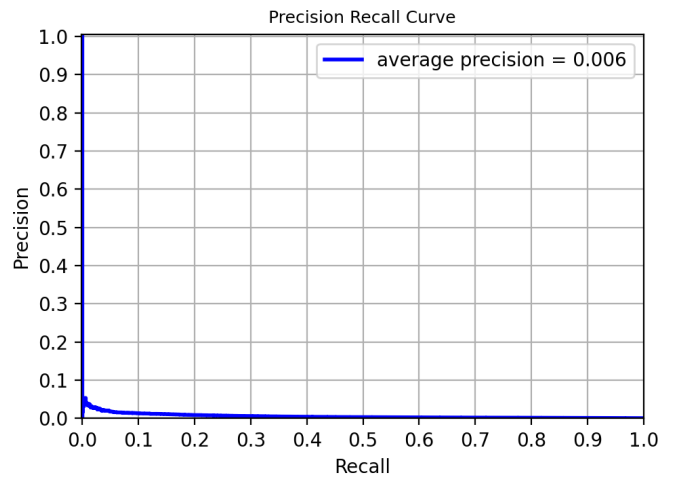

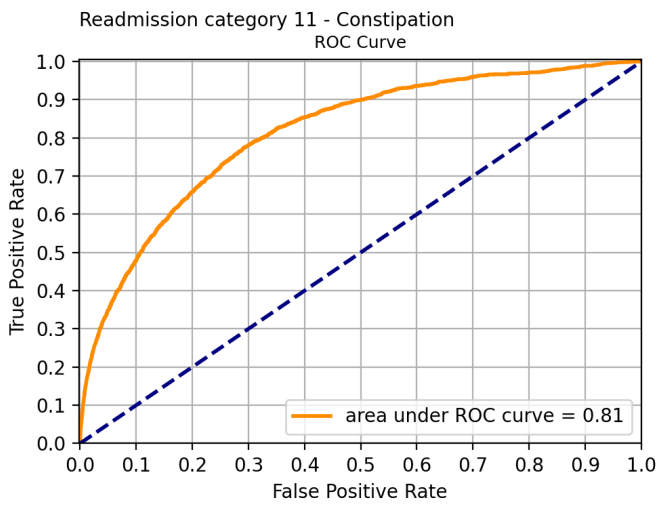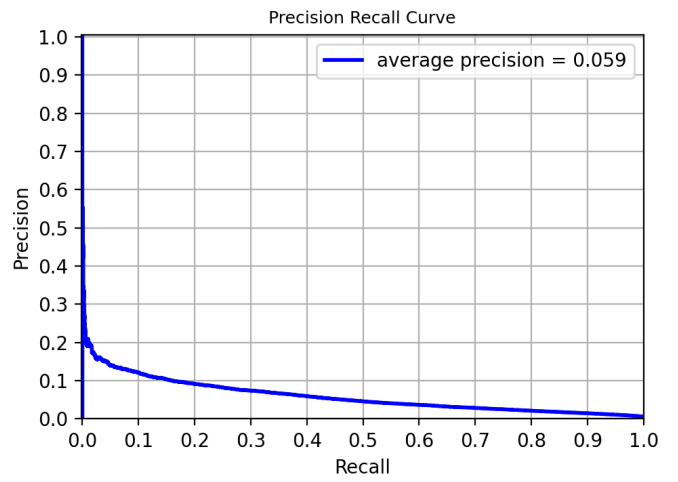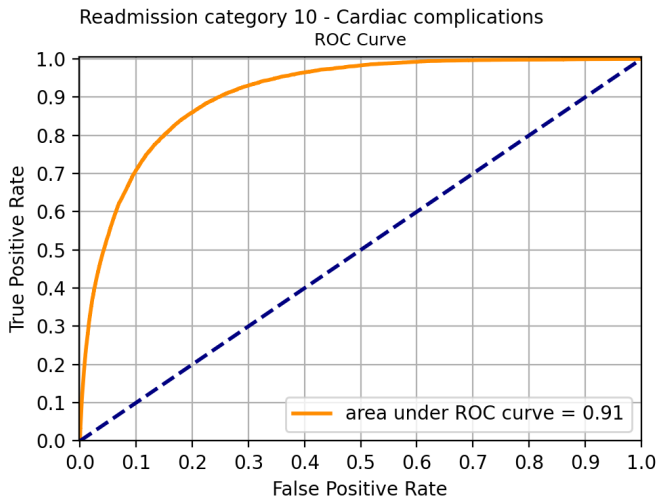## AHR11 - Constipation
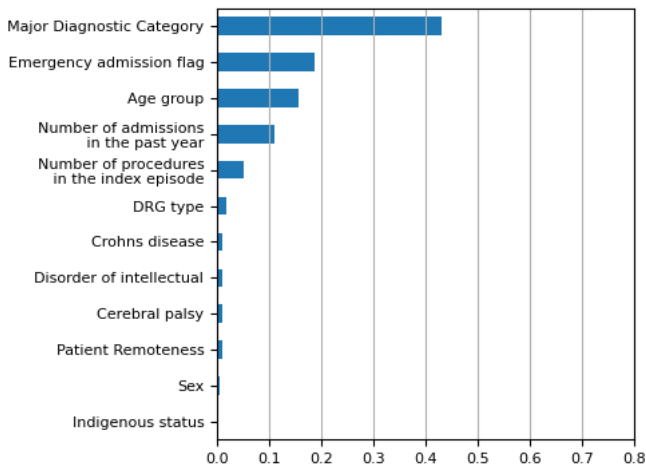
AHR12 - Nausea and vomiting
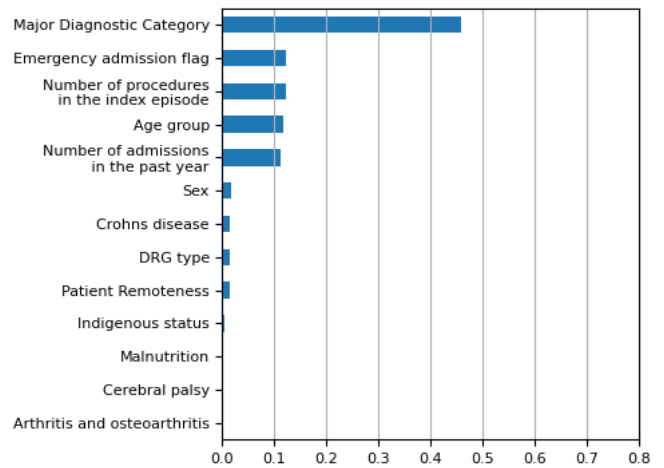
[9] Note that the x-axis is unlabelled due to being relative feature importance, a ranked arbitrary unit describing risk factor discriminatory power which depends on the specific model it is referring to.

Appendix H: Model fit curves

Readmission category 1 - Pressure injury
ROC Curve / Precision Recall Curve (average precision = 0.006; area under ROC curve = 0.91)

Readmission category 2 - Infections
ROC Curve / Precision Recall Curve (average precision = 0.017; area under ROC curve = 0.76)

Readmission category 3 - Surgical complications
ROC Curve / Precision Recall Curve (average precision = 0.028; area under ROC curve = 0.92)

Readmission category 4 - Respiratory complications

Readmission category 5 - Venous thromboembolism

Readmission category 6 - Renal failure

Readmission category 7 - Gastrointestinal bleeding

Readmission category 8 - Medication complications

Readmission category 9 - Delirium

Readmission category 10 - Cardiac complications

Readmission category 11 - Constipation

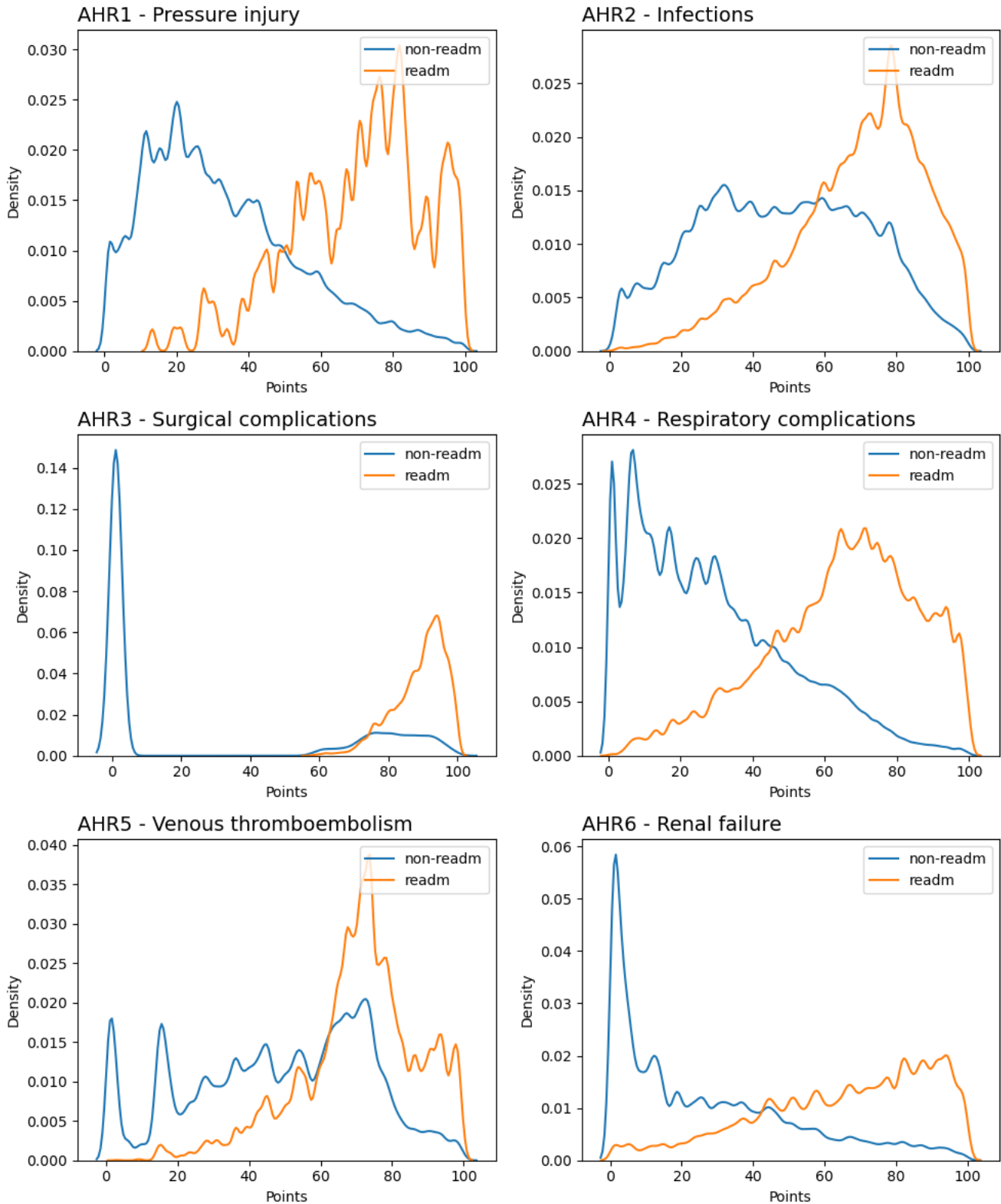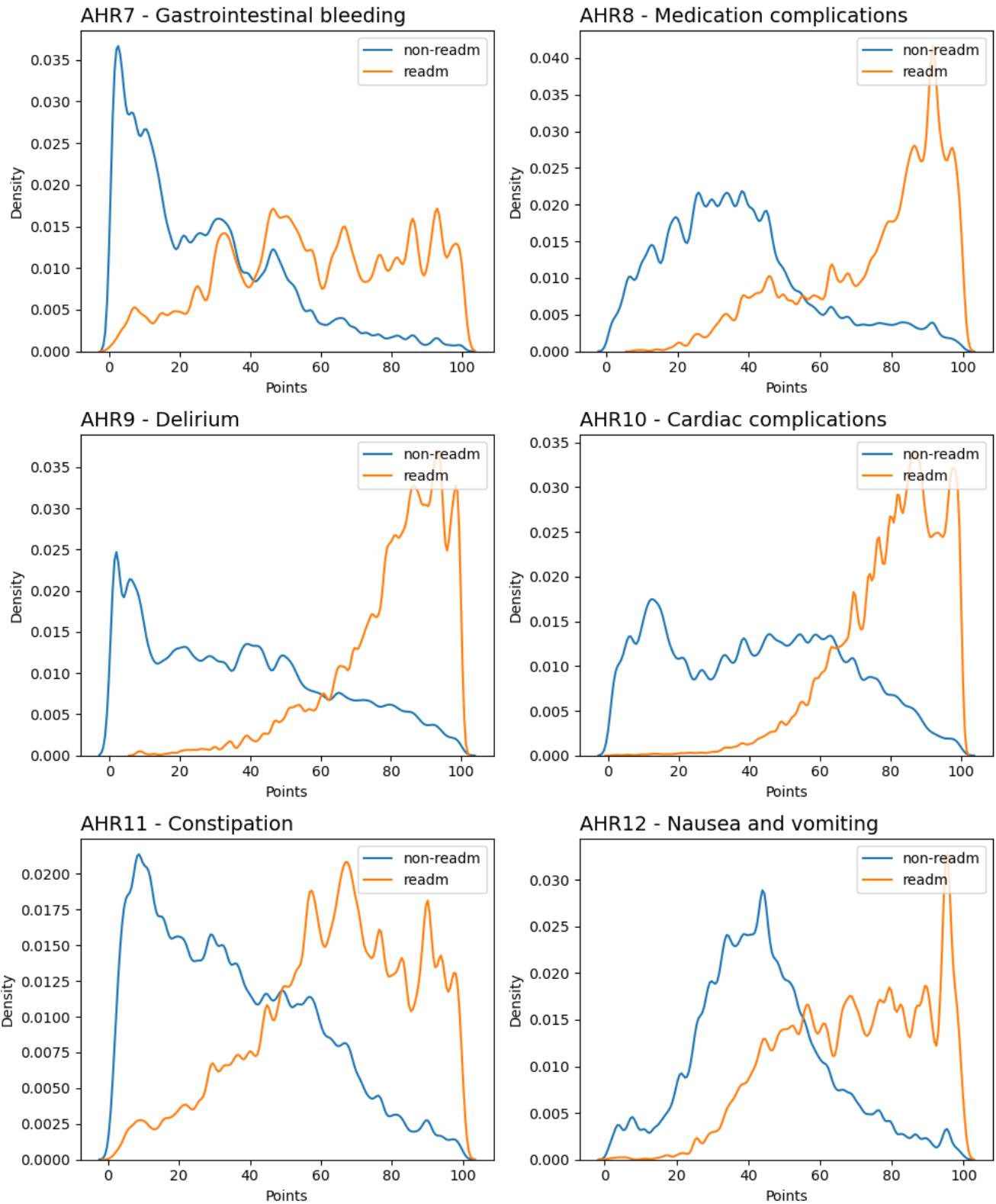## Readmission category 12 - Nausea and vomiting

Appendix I: Model complexity distributions

Complexity distribution characteristics

Based on the above figures, in general, the distribution of readmissions overlaps with that of non-readmissions, but the major episode-density of non-readmissions tends to be at lower complexities than those of readmission episodes. This is consistent with AHRs tending to occur in episodes with higher complexities.

Appendix J: Change tracker

Table J1: The description of key changes to the AHR model during NEP cycles

NEP year	AHR list version	Description of key changes
NEP21	1.0	Introduction of AHR risk adjustment.
NEP22	1.0	N/A
NEP23	2.0	N/A
NEP24	2.0	Commenced the process of updating the ICD-10-AM codes to 12th edition; these codes underpin the identification of Charlson comorbidity conditions and standalone risk factors.
NEP25	2.0	Updates to risk flagging ICD-10-AM codes to prepare for ICD-10-AM 13th Edition and to remove outdated or otherwise unnecessary codes.

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