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Postgraduate Thesis

Defining and Evaluating an Operational Definition of Potentially Preventable Hospital Readmission

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Master of Research

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Declaration of Authorship

I, Aidan O'Brien, declare that this thesis titled, 'Defining and Evaluting an Operational Definition of Potentially Preventable Hospital Readmission' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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Abstract

Faculty of Medicine and Health Sciences
Australian Institute of Health Innovation

Master of Research

Defining and Evaluting an Operational Definition of Potentially Preventable Hospital Readmission

by Aidan O'Brien

Readmissions to hospital are a globally recognised problem. Currently no standardised validated definition for potentially preventable hospital readmissions exists. Instead, various forms of unplanned hospital readmission rates are used as indicators of the quality of care received in hospitals. This reduces the reliability of current readmission measures that is expected from high-quality indicators of care.

The aim of this research project was to develop, operationalise, and validate a definition of potentially preventable readmission that can be used as part of a readmission performance indicator. An algorithm was used to determine preventability from hospital administrative data. This definition was validated using an audit of readmissions in the Northern NSW Local Health District. Preventability due to hospital factors was accurately determined by the algorithm. Patient, transition to community care and community care factors could not be properly identified from hospital administrative data.

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And my parents who have always encouraged me to challenge myself and increase my education...

And most importantly, Christina, without whose love and patience I wouldn't have been able to write this thesis at all. And for the limitless tolerance of my nocturnal writing hours.

Thank you.

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Abbreviations

APEDDR	**A**dmitted **P**atient **E**mergency **D**epartment **D**eath **R**egistry
APDC	**A**dmitted **P**atient **D**ata **C**ollection
BHI	**B**ureau of **H**ealth **I**nformation
CHeReL	**Ce**ntre for **H**ealth **Re**cord **L**inkage
CMS	**C**enters for **M**edicare and Medicaid **S**ervices
DRG	**D**iagnosis **R**elated **G**roup
LHD	**L**ocal **H**ealth **D**istrict
NHS	**N**ational **H**ealth **S**ervice
NNSWLHD	**N**orthern **N**ew **S**outh **W**ales **L**ocal **H**ealth **D**istrict
NSW	**N**ew **S**outh **W**ales
PPHR	**P**otentially **P**reventable **H**ospital **R**eadmission
PPR	**P**otentially **P**reventable **R**eadmission
SAPHaRI	**S**ecure **A**nalytics for **P**opulation **H**ealth **R**esearch and **I**ntelligence
UHR	**U**nplanned **H**ospital **R**eadamission
U.K.	**U**nited **K**ingdom
U.S.	**U**nited **S**tates of America

Chapter 1

Introduction

1.1 Nomenclature

A note on nomenclature in this thesis must be stated regarding three similar terms: indicator, definition, and data definition. In the context of this thesis an indicator (performance or clinical) is a form of measurement that is in use in the healthcare system. For example: unplanned hospital readmissions within 28 days is a performance indicator used to monitor, communicate and, in some cases, penalise hospital performance. The indicator does not specify the characteristics of the measure (for e.g. definition of 'unplanned' admission, excluded conditions, or if the readmission is to the same hospital), which can be changed over time to better reflect progress in the field. A definition is the detailed representation of an indicator. It should be precise enough to describe the inclusion and exclusion criteria so that it can be operationalised for use in specific healthcare systems. A data definition (or operational definition) is the operationalisation of this definition, with properties such as included or excluded diagnosis or procedure codes [1], the exact flags in the patient record [2], or the algorithm used to determine inclusion [2, 3]. The major difference between a definition and data definition is that a definition is implementation agnostic.

1.2 Background

Readmissions to hospital are a globally recognised problem, and represent a significant burden to patients and a huge cost to health care systems. In the United States readmissions annually cost Medicare over $17 billion and on average $7200 was spent on each potentially preventable readmission [4, 5]. While in Australia lowering the overall readmissions rate from 2.2 percent to 0.53 percent in 2012 had an estimated savings of $100 million to the Australian healthcare system [6].

Research into predicting and preventing unplanned hospital readmissions has been formally conducted from at least the early to mid 1980s [7–9]. Over time, it has developed to the point where readmission indicators are being used in healthcare systems in a range of countries and even resulting in financial penalties to underperforming hospitals in the United States [10–14] and the United Kingdom [15]. At the core of this research is the finding of validated operational measures of preventable readmission [16]. Although prone to low inter-rater reliability, the chart review process is considered the "gold standard" in determining the preventability of a readmission [17–19]. However, chart reviews are resource-intensive and not realistically extendable to the scale of evaluating every readmission individually in a healthcare system [20]. In contrast, automated methods can provide faster, more cost-effective alternatives.

This results in a multi-pareto problem, where optimising across multiple competing objectives: cost, time, accuracy and relevance to patient outcomes is at stake. While the accuracy of an indicator, that is, how often it correctly identifies potentially preventable readmission, can improve with manual chart review, performing large scale chart reviews would be a herculean task when done at the scale of an entire state or national healthcare system. It would involve extreme costs, along with delays in recording the data, as every chart review takes time from clinicians being able to treat patients. Furthermore, the subjectivity of what constitutes preventability requires more than one reviewer to look at the same record, together with an estimate of the consistency and inter-rater reliability of the findings. However, fully manual chart reviews is the only method to analyse an entire patient record in some hospitals, where they use paper records. In New South Wales only 50 percent of hospitals had a compatible electronic medical record by the end of 2016 [21]. Until patient data is fully digitised in compatible formats, retrieval of records and algorithms will not be possible. The relevance to patient outcomes depends on what the indicator is meant to measure. Unplanned readmission is an easily measured proxy for those readmissions that could have been prevented, where time and cost factors due to manual chart reviews prohibits widespread audits to use a more relevant indicator.

1.3 Problem Statement

Currently no standardised validated definition for potentially preventable hospital readmissions (PPHR) exists within Australia and the international countries that were surveyed as part of this thesis [22]. Instead, various forms of unplanned hospital readmission rates are used as indicators of the quality of care received in hospitals [1–3]. Unplanned readmissions are currently used as an indicator of potentially preventable readmissions due to unplanned readmissions possibly reflecting 'less than optimal initial patient management' [23]. However, studies have shown that the range of potentially preventable readmissions lies between 5% and 79% of unplanned readmissions [5, 14, 16, 24]. This reduces the reliability of current readmission measures that is expected from high-quality indicators of care.

1.4 Aim

The aim of this research was to develop and evaluate a hierarchical definition of potentially preventable hospital readmission to support a readmission performance indicator for NSW Health. This proposed hierarchy of definitions moves from all-cause readmission (the easiest to operationalise), through all-cause unplanned readmission, to potentially preventable readmission (the most challenging to opearationalise). This hierarchical aspect conceivably allows for smooth transitions from higher levels of the hierarchy where relevant data is already available to lower, more relevant levels, as data availability and quality improve over time. Optional filters to modify inclusion/exclusion criteria were included to facilitate comparisons with other existing indicators. Comparisons against an existing clinical audit of chart-reviewed unplanned readmissions allowed for the evaluation of how well the indicators worked, and which preventable factors could be identified reliably from hospital administrative data.

1.5 Methods

To provide evidence and justification for the choices made when developing a performance indicator for NSW Health, an examination of the current standards in Australia, the United Kingdom (UK) and the United States of America (US) was conducted, comparing the methods used to measure readmission rates, plus the strengths and weaknesses of each nation's readmission indicator. Then, a literature review of the current state of research into potentially preventable readmission highlighted how cutting edge research in the field defines preventability in the context of hospital readmission, as well as the list of conditions and patient characteristics (e.g. age, cancer treatment or transplant patient) commonly excluded from readmission indicators.

The literature review also identified a validated algorithm (SQLape) for the identification of potentially preventable readmission from hospital administrative data. This algorithm was modified and customised for New South Wales. Findings from the new algorithm (pyLape) were compared against a clinical audit of chart-reviewed unplanned readmissions conducted during June and July of 2014 in the Northern New South Wales Local Health District (NNSWLHD). The linkage between this audit and the NSW Admitted Patient Data Collection was performed by the NSW Centre for Health Record Linkage (CHeReL). Hospital admissions one month before and one month after the study period were also included in the linked dataset to capture index admissions and follow-up care. Ethical approval for the project and use of patient data was granted by the NSW Population & Health Services Research Ethics Committee (AU RED Reference: HREC/16/CIPHS/43).

1.6 Results

The current Australian unplanned readmission indicator measures "Unplanned and unexpected hospital readmission to the same public hospital within 28 days after selected surgical procedures". When compared to the UK and the US definitions, only the Australian definition excludes readmissions to other hospitals. This has significantly underestimated the reported rates of unplanned readmission, as can be seen when comparing the figures reported by NSW Health with those reported by the Bureau of Health Information (BHI), which utilises a definition similar to the US indicator. To facilitate benchmarking and comparisons across different definitions the incorporation of four types of filters in the readmission indicator were proposed: healthcare layer (hospital, region, or national), patient inclusion/exclusion criteria (e.g. age), data quality inclusion/exclusion criteria (e.g. missing records), and preventability factors (e.g.hospital factors). Using these filters along with the hierarchical model allows for easy comparisons among proposed indicators and provides NSW Health with a platform for planning data gathering required for future improved performance indicators.

During the study period, there were 460 unplanned hospital readmissions in the NNSWLHD. The rate of all-cause unplanned potentially preventable readmission was 16.7 percent. 10 were listed in the audit as due to hospital factors, 13 were associated with patient factors, only 2 were associated with transition factors, a mere 3 were associated with community care factors and 46 were other or unidentified (where the audit records did not list the cause that the clinician determined to be preventable) factors. When compared against the findings from the audit, the proposed algorithm to identify potentially preventable readmissions, pyLape, was good at detecting hospital factors (sensitivity=0.71 and specificity=1.00). However, pyLape's sensitivity was poor in the identification of all other preventable factors, with a sensitivity=0.13 and specificity=0.97 for all-cause unplanned potentially preventable readmission. This was expected since patient and community factors are not represented in hospital administrative data.

This research was limited by the size and quality of the NNSWLHD's audit. There were only 109 records determined to be preventable, of which only 77 were kept for analysis once clinician opinions and duplicates were accounted for out of the 460 readmission records for the NNSWLHD. The transition to community care and community care factors had two and three patients identified respectively, greater numbers are needed to develop and validate an algorithm capable of identifying these factors. Furthermore, many records did not have additional notes indicating preventable factors of readmission. It is hypothesised that using the methodology utilised in this research study with a larger higher quality audit combined with more extensive electronic medical records from patients will lead to improved validated indicators of potentially preventable readmission.

1.7 Thesis structure

- **Chapter 2** provides a review of the existing performance indicators of unplanned hospital readmission in Australia and internationally, along with their corresponding data definitions, and whether any penalties in place impact readmission rates.
- **Chapter 3** contains a systematic literature review and analysis of existing definitions of potentially preventable hospital readmission. Once the common factors between existing definitions and indicators are identified, a model for developing future indicators based upon the requirements of the healthcare agency and the limitations of the data is developed and explained.
- **Chapter 4** proposes a performance indicator for New South Wales and Australia for potentially preventable hospital readmission based upon the model proposed in Chapter Three. A full explanation of the SQLape algorithm and modifications for Australian datasets is given, prior to using the Australian variation as validation of the proposed performance indicator, benchmarking the algorithm's performance against that of a manual chart review conducted previously in New South Wales.
- **Chapter 5** concludes the thesis, summarising the analysis of current unplanned readmission measures and the literature review. The contributions made by this thesis are also included within the chapter, along with future directions that this research can take.

Chapter 2

Current performance indicators of unplanned hospital readmission

2.1 Introduction

This chapter provides a review of the literature concerning existing data definitions and performance indicators of unplanned hospital readmission in Australia, the United States and the United Kingdom. The choice to use the U.K. and U.S. readmission indicators as a comparison to the Australian measure was due to two major points. Firstly, the U.K. has a similar nationalised healthcare system to Australia's Medicare in the National Health Service, while the United States also has a large single payer base in the (U.S.) Medicare. Secondly, both countries are at the forefront of hospital readmission research and policy, having introduced 'financial penalties' since 2011/2012 in the U.K. and 2012 in the U.S [15, 25, 26]. The comparison of how each healthcare system currently measures their readmission rate allows for understanding the current definitions.

2.2 Existing definitions and performance indicators

The Australian definition for unplanned hospital readmission is "*Unplanned and unexpected hospital readmission to the same public hospital within 28 days after selected surgical procedures*" [1]. Currently, these surgical procedures include: knee replacement, hip replacement, tonsillectomy, hysterectomy, prostatectomy, cataract surgery, and appendectomy during the index admission. The U.S. Centres for Medicare and Medicaid Services (CMS) defines its performance indicator as "hospital-level risk-standardized rate of unplanned, all-cause readmission after admission for any eligible condition within 30 days of hospital discharge"[27]. The CMS data definition includes only patients 65 years of age and above ($\geqslant 65$), and focuses upon five different diagnoses and procedures in the index admission: acute myocardial infarction, pneumonia, heart failure, chronic obstructive pulmonary disease and hip/knee arthroplasty. These diagnoses and procedures have some of the highest unplanned readmission rates and cost per readmission, which combine to create some of the most costly conditions for readmission[28–31]. By contrast, the U.K.'s National Health Service (NHS) definition does not check the diagnoses or procedures of the index admission and defines its performance measure as "*an emergency readmission that occurred within 28 days following discharge*" [2].

Although all three indicators take into account the fact that the hospital readmission was not scheduled, they do so in different ways. In Australia, the unplanned readmission indicator is purely based upon surgical procedures as listed above, but it includes patients of any age and only to the same hospital. The indicator doesn't account for readmissions after a clinical hospitalisation in addition to surgical events. The measure in Australia isn't risk standardised, but does exclude planned returns to hospital[1]. An in depth examination of the indicator gives a list of specific procedure codes that are included, which implicitly excludes readmissions due to trauma. This form of unplanned readmission indicator misses out on a portion of all readmissions. Section 2.3 goes into more depth, comparing the national indicator against measures based upon the CMS measure.

In the U.K., the NHS develops and releases the unexpected readmission indicator. The indicator is much more inclusive than the Australian indicator, in that it allows for all unplanned and unexpected returns to hospital, even those that may be unrelated [2, 32]. Unlike the Australian definition, it includes a return to any hospital within the U.K. and due to the lack of checking what the diagnoses or procedures during the index admission or cause for readmission were, implicitly includes both medical and surgical causes of readmission. To be classified as an unexpected readmission, a flag is set in the data on the readmission that the patient was not there for a planned appointment. One notable feature of the way that the NHS's indicator differs from both the Australian and United States indicators is that the admitting 'team' is recorded and based upon who referred or admitted the patient into hospital, the patient is included or excluded. These teams include the 'Mental Health' team, 'Maternity' team, et al. This is given by the admission method stored in the patient's records [2]. An obvious flaw to this is that if a patient is with a particular team and is then readmitted for a cause that the clinician noticed that was unrelated to the team's focus, the patient would be excluded. The way that these flags are combined in the readmission indicator is a simple piecewise algorithm, if they were unexpected and admitted via particular channels, they are included in the unexpected readmission rate [2].

In comparison to the Australian and U.K.'s indicators, the U.S.'s main readmission indicator was created for a specific portion of the population. The CMS use the indicator for measuring readmission rates for their Medicare services. Medicare in the U.S. is a single payer health insurance for Americans over 65 years of age or certain eligible disabled persons. This shapes the way the indicator is defined and developed. The first difference between the CMS readmission indicator compared to other nations is that it only measures patients aged 65 years or older, and who are not insured by Medicare from prior to the index admission until after the readmission [27]. The indicator also limits the types of index admissions that count towards measuring the readmissions rate. The CMS indicator states that it is all-cause unplanned readmissions, after one (or more) of the five diagnoses or procedures during the index admission as listed above[3, 27]. The readmissions are evaluated by an algorithm to determine whether or not they were considered planned or a trauma admission that obviously has no relation to the index admission and if so, are excluded from the measure [20, 27]. Certain types of care are considered 'always planned' according to the algorithm and are always excluded. The measure does also include any non-excluded readmission to an acute care hospital, allowing for all readmissions to be determined [27].

2.2.1 Discussion and comparison between national measures

All three data definitions are aimed at measuring the rate of unplanned or unexpected readmissions, with varying levels of specificity. The Australian data definition has specific surgical procedures in the index admission and specific readmission causes, the CMS data definition has specific medical diagnoses and surgical procedures with all-cause readmission with exclusions for planned readmissions, while the NHS data definition is the least specific of the three, with the method of readmission rather than the cause being measured. A high-level summary of the inclusions and exclusions to the different national measures is included in Table 2.1.

The three national indicators and their data definitions reflect the current focus of each nation's healthcare system regarding readmission. The United States has the highest amount of research dedicated to readmissions and has the most sophisticated of the three measures with case mix methods based upon comorbidities being utilised in the determination of readmission rates. Along with a focus on a limited number of conditions as the main cause (as determined from procedure and diagnosis codes) of the index admission, these main causes have the highest rate of readmission in the U.S. and were thus identified as needing to be minimised [27]. The all-cause unplanned hospital readmission rate used by the United States Medicare also utilises a sophisticated algorithm to determine whether a readmission was planned or not which considers some procedures always planned, scheduled procedures to be planned and acute illnesses to never be considered planned [20]. At the other end of the spectrum is the United Kingdom's NHS readmission measure, which includes both an indicator and the data definition in the same document. The requirements for the data definition are simple conditionals based upon duration between both admissions and simple flags set on the origin of each admission [32]. These simple flags use some assumptions to exclude certain populations (maternity entry and those admitted by the mental health team). The flag is set in the patient record if the readmission was unexpected and naively considers all unexpected readmissions to be indicative of preventability. In effect, it considers how a patient is readmitted to hospital rather than any specific conditions and their relationship to the previous admission. The Australian data definition falls partway between the two, it only measures readmissions after a limited number of surgical procedures that occurred during the index admission and only if the readmission is unplanned for a limited number of procedures that are assumed to be caused by complications in the index admission. The Australian measure is essentially a simple algorithm of whether the index admission had one of a list of procedures, and the readmission included at least one of a second list of procedures and it was unscheduled in the duration, it is defined as an unplanned hospital readmission. It contains an implied relationship of the two admissions due to the choice of procedures, however does not calculate individual patient's comorbidities. It is worth noticing that currently, only the Australian definition excludes readmissions to other hospitals. This is a reflection of the fact that until very recently, Australia did not have the infrastructure required to follow up patients across multiple acute care facilities. This has significantly underestimated the reported rates of unplanned readmission [33].

The more sophisticated measures of the United States and Australia are not perfect. Each includes its own assumptions to show that the two admissions were related. And all three tell the story of the unplanned rate, and may even have a strong correlation as to whether the two admissions were clinically related to one another [16]. This, however, does not mean that the readmission was *preventable*. Chapter 3 goes into depth on how current research determines preventability, what methods are currently in use and how to create a definition to measure it correctly.

As shown in Table 2.1 there is not a standard consensus between nations on what should be included on a broad scale. (Note that the U.K. has two durations, $\leqslant 28$

TABLE 2.1: Overview of National Measures

	Australia	**U.K.**	**U.S**
Duration (*days*)	$\leqslant 28$	$\leqslant 28$	$\leqslant 30$
Any Hospital	No	Yes	No
Unrelated Excluded	Yes	No	Yes
Clinical Conditions	No	Yes	Yes
Surgical Conditions	Yes	Yes	Yes
Operationalisation Method	ICD-10-AM	Flag	Algorithm
Financial Penalty	No	Yes	Yes
Readmission Rate	Approx. 1%	8-12%	18-22%

and $\leqslant 30$, however statistics are only externally available for $\leqslant 28$ and this was the measure included). These measures are all attempting to improve patient outcomes while also reducing the financial burden on the healthcare system due to costly readmissions, however readmissions to a different hospital still have a negative outcome on both aims. Australia is an outlier in that the measure doesn't account for readmissions after clinical index admissions. The points where all three diverge is the exclusion of unrelated causes of readmission and the operationalisation method as explained above.

2.3 Trends and distributions

As shown in Table 2.1 and in detail in Figure 2.1 the three different national measures all return different rates of readmission due to the different ways of measuring unplanned readmission. As detailed per year rates for U.K. hospitals was not available, their average rate is included in Table 2.1 but individual years are not shown in Figure 2.1. As the U.S. only measures patients over the age of 65, based upon the reasoning that they have a higher risk of readmission than the general population [28–31], this measure is thus likely to have a higher readmission rate than the other countries, further, the U.S. measure only measures those conditions that have both a high readmission rate and high cost [28, 30] which will skew the data. The Australian readmission rate is not an All-Cause rate like the U.S. and U.K. rates and only considers a readmission when the patient is readmitted where "the unplanned and/or unexpected readmissions are limited to those having a principal diagnosis of a post-operative adverse event for which a specified International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM) diagnosis code has been assigned. This does not include all possible unplanned/unexpected readmissions" [1]. As this does not consider clinical admission diagnoses and is focused upon surgical complications, the rates are expected to differ substantially. The Bureau of Health Information (BHI) is a NSW organisation that provides independent reports about NSW's public healthcare system.

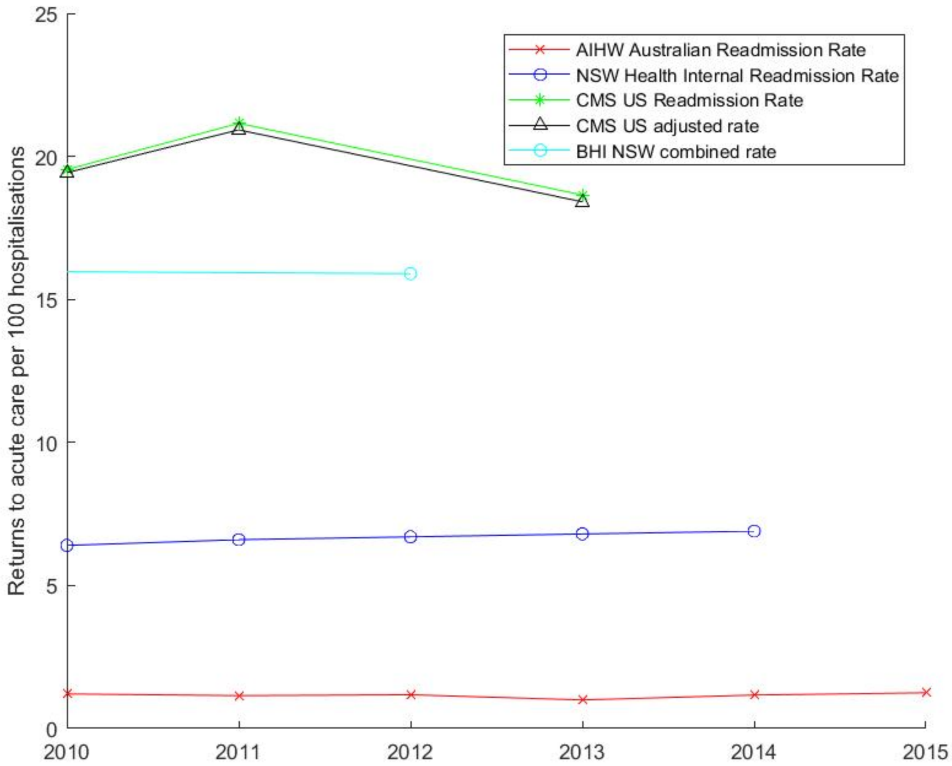


FIGURE 2.1: Comparison between BHI reported rates 2003-2012, NSW Health Internal reporting 2010-2014, Australian Institute of Health and Welfare reporting 2010-2015 and Centers for Medicare and Medicaid Services reporting 2010-2013

The last entry into Table 2.1 is a comparison between the averaged or combined rates from the measures. The graph shows the differences that having different indicators can have on a healthcare system's reports. As these reports describe performance, they are an important part of shaping policy and funding. The average rates for each nation are compared over a five to ten year period depending on what was available for retrieval. The United States has the highest of these measures, with a rate of approximately twenty percent. This is in comparison to the United Kingdom where the Unplanned and unexpected readmissions has a rate of around ten percent. While these numbers are substantially different, they clearly show the effect that removing index admissions which have a low risk of readmission and only including members of the population that have a raised risk of readmission due to age has. Both of these measures however stand in stark contrast to the readmission rate reported nationally in Australia, which is approximately one percent.

Examination of data from New South Wales is conducted to understand where the difference arises between the measures, as NSW is the largest healthcare system in Australia. We have access to NSW Health readmission reports and the BHI's reports using NSW Health's de-identified dataset. The BHI reports utilise the same definition for Unplanned Readmission (All-cause for selected conditions) to all hospitals as the United States and have a similar figure to the U.S. with differences small enough to be explained by differences in the population [33].

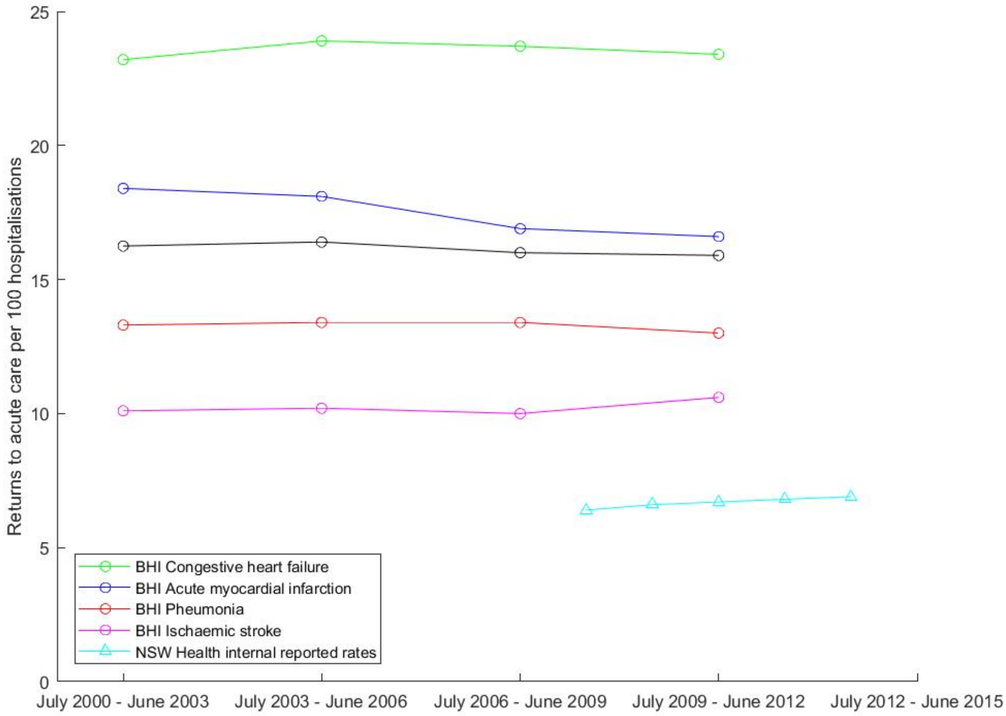


FIGURE 2.2: Comparison between BHI reported rates 2003-2012 and NSW Health Internal reporting 2010-2014

As we can see from the graph in Figure 2.2, there is a large difference between the internal reporting from NSW Health and BHI due to the way readmissions are measured. BHI is utilising an internationally validated method of measuring readmissions on NSW Health data and results in similar rates to international measures, BHI's method is an adaptation of the same method utilised in the United States, adjusted to Australian diagnostic and procedural codes [33]. Below are the BHI results in their original separate rates based upon medical condition during the index admission. This matches the way that the United States Medicare reports their readmission rates. As shown in figure 2.1, the readmission rates are similar, with expected differences due to population and socioeconomic factors.

2.4 Discussion

The three national indicators and their data definitions reflect data availability and the current focus of each nation's healthcare system regarding readmission. The Australian indicator measures "Unplanned and unexpected hospital readmission to the same public hospital within 28 days after selected surgical procedures" following a simple algorithm that relates the index admission with the readmission using procedure codes. The current Australian definition also excludes readmissions to other hospitals and therefore has significantly underestimated the reported rates of unplanned readmission [33].

Prior to 2011, when the NHS introduced penalties in the U.K., the NHS rewarded hospitals for good performance. Although since 2011, the readmission rate has decreased, this decrease appears to be in line with existing trends from prior to 2011 [15]. Australia has reported a general trend of readmissions lowering from at least 2006 [6] (earlier data was not available), however since 2010 this rate has stabilised to hold steady [6]. The plateau in the readmission rate both with rewards and penalties leads towards attempting to find another solution to the problem. In Chapter 3 we will be discussing how to define Potentially Preventable Readmissions, with the purpose of measuring these readmissions so that a more accurate picture of hospital performance can be realised.

Chapter 3

Definitions of Potentially Preventable Hospital Readmissions

3.1 Introduction

In Chapter 2 we examined the way national healthcare systems in Australia, the U.S. and the U.K. defined their unplanned or unexpected readmission indicators. Each healthcare system had a different way of measuring their performance indicator. In this chapter we examine the literature for definitions and indicators relating to readmissions, from the most basic, all readmissions, unplanned readmissions and through to the more sophisticated potentially preventable readmissions. The inclusion of all three types of definition is due to studies often comparing one definition against another.

Currently no standardised definition for a potentially preventable readmission exists [22] much like the lack of a standardised international definition of unplanned readmissions as explained in Chapter 2. In reviewing the literature, definitions fall into two broad categories: utilising the national standard of unplanned readmission as a base that is modified to account for potentially preventable, or the definitions used in a particular study are created for the study based on the available data concerning potential preventability or tools in use. Potential preventability has a range of definitions based upon the focus of the healthcare organisation's objectives regarding patient care and the available data. One the one hand, studies where the objective is to measure or improve hospital performance tend to exclude patient and community care actions from causing preventable readmissions [22]. On the other hand, those studies that are examining preventability for the whole healthcare system include community services and the actions of carers [11]. Bringing these competing interests into harmony will improve comparisons between studies.

After reviewing the literature it is clear that the data needed to achieve the aims of the definition needs to be included within the definition, especially where seeking to determine preventability due to factors outside the hospital environment and in the greater healthcare system. Two major results occurred with this, where researchers either excluded factors that were not able to be retrieved in their dataset, or conducted a manual chart review and retrieved the information from the patient's clinical notes.

In consultation with stakeholders at the NSW Ministry of Health, an indicator is developed based upon the literature review for validation and use in NSW Health research projects.

3.2 Literature Review

3.2.1 Literature Search

We developed a systematic review protocol to identify studies which described readmission definitions. This included definitions for all readmissions, unplanned and potentially preventable. This protocol was lodged with PROSPERO and approved prior to commencing the review [34]. As shown in Figure 3.1 we searched the MEDLINE, EMBASE and CINAHL databases for all records until July 2016. Titles and abstracts were reviewed for any cases where readmissions were described as unplanned or preventable (or "avoidable", "emergency", "needless", "unnecessary", "unscheduled", and "urgent"). Unplanned readmissions were included due to their frequent comparison to potentially preventable readmissions, with the differences between unplanned and potentially preventable being examined in some studies. Those citations which fulfilled the requirements were then subjected to full text review and were included in the review if they stated the definition in use. The references of included papers were reviewed to identify the original definition and further eligible articles. If an article referred to a definition from a previous reference, the original source was kept and if the article only repeated a definition the article was excluded, unless it was a) a validation study of the definition or b) contained an additional definition(s) which was not otherwise retrieved. Each step was conducted by two reviewers and if there was a difference of included papers between reviewers, each item was discussed individually and then included or excluded based upon agreement.

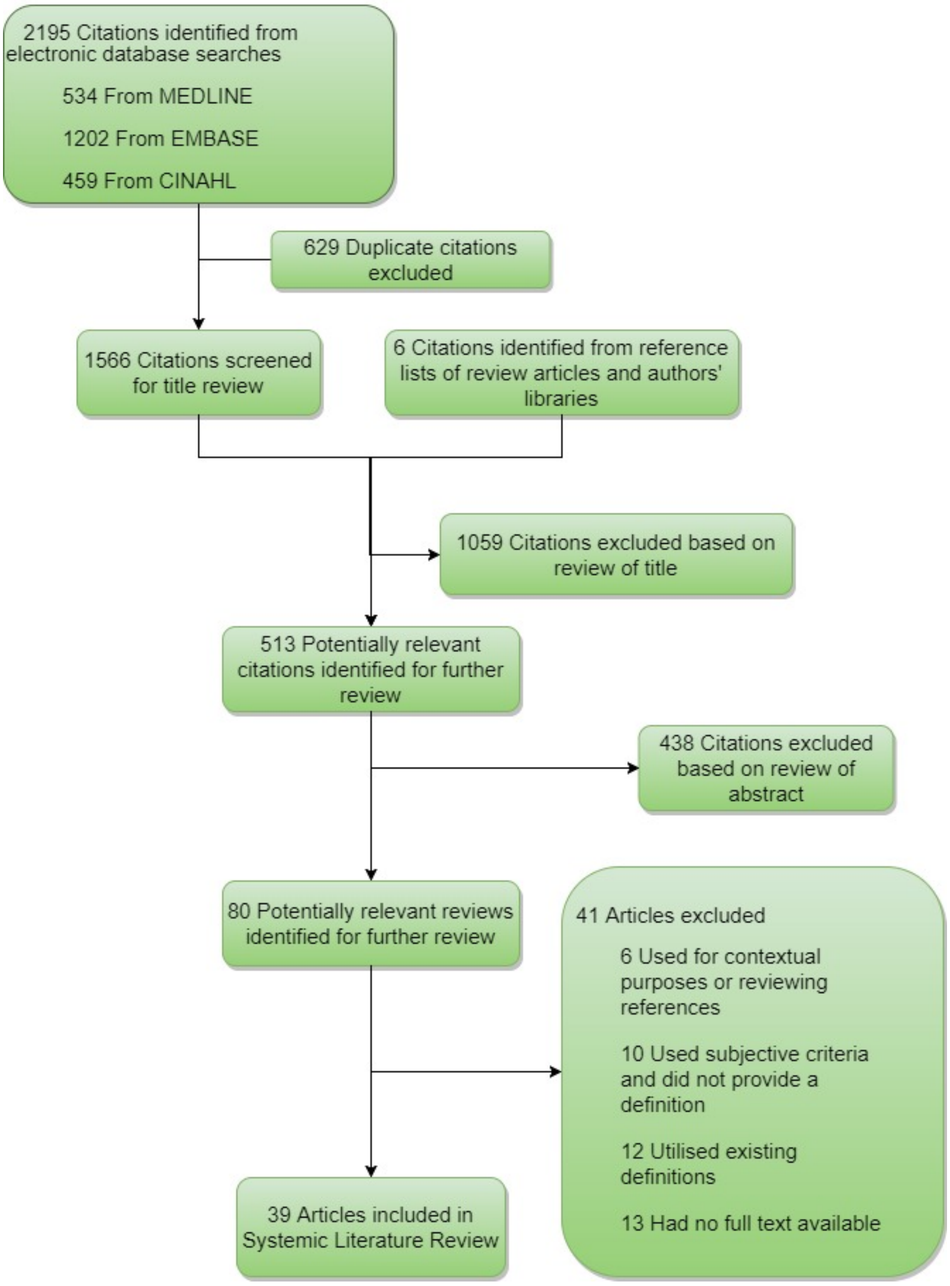


FIGURE 3.1: Systematic Review Flowchart

3.2.2 Data Abstraction

Data abstracted from each paper included basic study information (cohort study used, country of study), level of definition layer (hospital, region, or national), level of definition category (all, unplanned, or preventable, etc.), patient inclusion or exclusion criteria (age, gender, disease, etc.), data quality inclusion and exclusion (missing records, left against medical advice, etc.), causes of preventability, and rates of readmission and preventability.

3.2.3 Findings from the Literature Review

39 studies and national standards resulted in the 61 definitions included in the review as shown in Table 3.1. The number of definitions exceeds the number of studies because many articles included multiple different definitions and compared them against one another. Basic descriptive features for each study were retrieved. To explore definitions the type of definition was categorised based on similar features. If the inverse of the category was defined within a study it was included in the review, for example a study defining or identifying planned readmissions would be included as unplanned readmissions as it implicitly defined unplanned readmissions as the exclusions from planned readmissions. Some definitions were extensions or modifications of another definition, the most common to be modified was the United States Medicare All Cause Unplanned Readmissions definition. Modifications were often extensions of eligible population (i.e. Patients of all ages rather than just over 65 years) or adjusted due to missing or additional data.

Often a definition was tested under different conditions rather than its initial description, with changes to geographical area being a common example of this behaviour. For example, a definition that was designed to measure patient readmissions to the same facility would be used in a study which tracked readmissions to any hospital in a region, healthcare provider network or nation. Additionally a single study compared the definitions of unplanned versus potentially preventable against one another without limiting the readmission to a specific facility level [62]. The layers referred to in Table 3.2 are at which definition layer readmission was examined, for example if the definition stated that it included all readmissions to the same hospital as the index admission, it would be classified at the hospital layer, while a readmission to any hospital in a geographic area smaller than a nation was classified as Regional (i.e. State or health districts) as in the review the healthcare systems would often cross state borders in privately run systems while government systems would adhere to their boundaries. When looking at the regional layer or above, it is expected that readmissions to any hospital in the region are accounted for, however while is not is always the case, in crafting an indicator one should aim to have as accurate measurements as possible.

As part of each study's analysis certain patients were excluded, either because they were no longer relevant to the study (patient mortality prevents readmission) or the patient's choices prevented medical care being given (leaving the hospital against medical advice), or due to missing or erroneous data. Not all definitions included the exclusion criteria in the published study.

TABLE 3.1: Number of Definitions and Categories of Conditions that Excluded Patients

Definition	**No. Definitions**	**References**
All Readmissions	9	[12, 22, 35–41]
Unplanned	34	[10, 23, 35–39, 42–51]
		[1, 2, 11, 13, 14, 20, 27, 52–61]
Poten. Preventable	18	[22, 23, 35, 40–44, 62, 63]
		[10–12, 14, 39, 51, 60, 64]
Total	61	
Patient Exclusions:		
Exclusion	**Sub-categories**	**No. of Exclusions**
Patient	Left Against Med. Adv.	13
	Patient Death	10
Record Coding	Missing Data	4
	LoS $<$ 24 hours	5
	Transfer facility	17
	Duplication	3
Cohort Exclusions:		
Exclusion	**Sub-categories**	**No. of Exclusions**
Age	$<$ 65/70 years old	4
	$>$ 18 years old	2
	$<$ 16/18 years old	7
	$<$ 4 years old	1
Maternity	Maternity/Neonatal	9
Cancer Related	Cancer/Chemo- /Radiotherapy	12
Other Diseases	Non-AMI, PN, HF	3
	HIV	2
	Unrelated admissions	2
	All other excluded	7
Acute Procedures	Transplants	3
	Trauma	6
Scheduled	Dialysis Readmission	5
Organisational	Social Causes	5

TABLE 3.2: Geographical Area or Definition Layer that definitions were examining

Definition Layer	**Number of Studies**
Patient	1
Hospital	43
Regional	16
National	5
Multiple	2
Definition Review	2
Unspecified	1
Total	66

Further the cohorts being studied were also a cause of inclusion/exclusion. An example of the definition of the CMS All-cause Unplanned Readmission measure shows that only patients with Acute Myocardial Infarction (AMI), Pneumonia (PN), Heart Failure (HF), and after 2012, Chronic Obstructive Pulmonary Disease (COPD) and Stroke during the index admission are included [10]. In keeping the cohorts the same, compared definitions in the same study often excluded the same patients.Further, there were also limitations due to the available data. For example, definitions used at pediatric hospitals only included patients under the age of 18 [22, 51]. A major exclusion category was based on certain procedures, such as cancer based treatments (chemotherapy and radiation therapy), or other major invasive surgeries such as transplants. Additionally Maternity admissions and births were frequently excluded. The full breakdown is shown in table 3.1.

In the papers included, not all were studying preventable readmissions, thus did not list potential causes of preventability. Table 3.3 shows the causes explicitly listed which were given in an article. A significant portion of listed avoidable causes (at 29.3%) was Incorrect Procedure Management, which included: discharge procedures, failure of follow-up care, incorrect readmission/"path of least resistance", incorrect documentation, coordination errors, and other systemic error variations. Other major categories include adverse events and/or complications, relapse of index condition or a clinically related diagnosis on readmission. The names of the 'avoidable' causes in Table 3.3 were taken directly from the papers that they were mentioned in. It is possible for a potential cause to fit into multiple categories of preventable factors at this level. For example, a readmission identified as Incorrect Procedure Management is potentially a hospital or a transition factor due to how inclusive the term is with both 'discharge procedures' (transition) and 'incorrect documentation' (hospital) being subcategories of Incorrect Procedure Management.

From these causes, it is clear that there is a substantial difference between definitions, which makes current direct comparisons difficult. With 61 total definitions, eighteen of which defining preventable readmissions, there is some overlap. As even the measurement level differed between definitions (for example, hospital-wide versus region wide performance), it underscores how fractured the current state of definitions is.

Within Table 3.3 there are multiple factors that are the root cause of the readmission. These can be broken down into four main categories. However, they may fall into multiple categories. There are those causes that could have been avoided had the hospital acted differently, such as Incorrect Procedure Management or Surgical Complications.

TABLE 3.3: List of Potentially Avoidable Causes of Readmission

Category	**Potential Cause of Readmission**	**No. Inclusions**
Any	Unresolved Index Condition	6
Any	Readmission diagnosis clinically related	4
Any	Flagged as Unplanned/Emergency in data	3
Hospital	Unresolved Medical Issue	6
Hospital	Medical Complications	17
Hospital	Surgical Complications	10
Hospital	Drug Side Effects	4
Hospital	Incorrect Index Assessment	7
Hospital	Non-specific adverse event	2
Hospital, Transition Community	Incorrect Procedure Management	39
Patient	Psychological problem	6
Patient, Community	Relapse or aggravation of a previously known affection(s)	15
Patient, Community	Social problem	6
Patient, Community	Drug or Diet non-compliance	8

While patient factors leading to readmission includes Drug or Diet non-compliance. Avoidable causes due to community care could include certain social problems or non-compliance if the patient doesn't have the resources in the community to comply. And the final category is transition factors, where the avoidable cause is due to transitioning from the hospital into community care, which is often procedural, either in incorrect procedures occurring or insufficient handover between hospital staff and community carers or patient education.

3.3 Summary of Literature Review

From the analysis of the literature, it was clear that there was a hierarchy of definitions. Where one definition was a subset of others as shown in Figure 3.2 below. For consistent naming within the flowchart, only additional terms were added as each category became more refined. Within the categories below, there was substantial crossover between the Emergency Readmissions and Related Emergency Readmissions categories. Often Unplanned Readmission measures contained aspects of both. Fully related readmissions would only include those readmissions which had a diagnosis which is reasonably related to the index admission. This is in contrast to the CMS All-Cause Unplanned Readmission measure, which excludes some acute conditions, but the readmission does not need to be specifically related to the index admission.

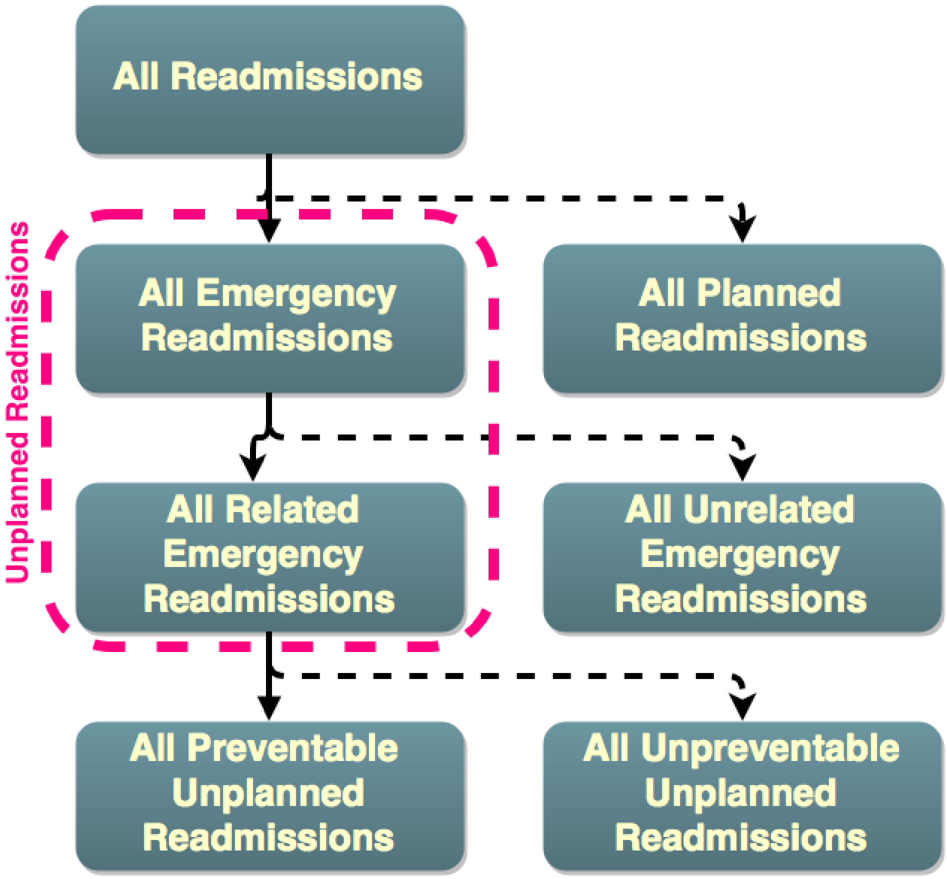


FIGURE 3.2: Readmission Hierarchy Flowchart

3.4 Stakeholder involvement

The public healthcare system within NSW has significant interest in improving patient quality of care and minimising operating costs. In consultation with NSW Ministry of Health representatives, the requirements of what outcomes needed to be measured from a reporting and operational perspective were established. Extensive meetings were conducted within the System Reporting Branch, Data Analysis, Clinical Excellence Commission and Directors from the Central Coast and Northern NSW Local Health Districts to determine which aspects of the literature were relevant to the state of the NSW healthcare system and performance measurement. The stakeholders wished for a measurable indicator that was able to analyse the performance of the whole healthcare system and individual hospitals. This would empower the healthcare system to improve patient outcomes, which is their main objective for the readmissions indicator. During stakeholder meetings it was made clear that without more information on patient behaviour and conditions outside the hospital becoming available and linked to the existing datasets, only hospital factors would be measurable in the short term.

The above stakeholders had previously conducted their own research into UHR, along with re-designing their discharge planning procedures in an attempt to lower their unplanned readmission rate. Part of this research involved conducting an audit on UHR in the NNSWLHD in 2014, the output dataset from this audit was supplied and is discussed in depth in Section 4.3.2. Additionally, LHDs were seeking greater insights into where to focus future resources, in areas such as patient decision, integrated care, GP services, health literacy with an interest in knowing exactly which factors were identifiable. Stakeholders also provided information on datasets available to NSW Health researchers that would potentially contain insights into readmissions.

Once studies attempt to identify preventable readmissions, they clearly stated the interrelated nature of the readmissions, as well as listed preventable causes. However, the definition of preventable causes was not always clear cut, often during studies which involved chart review, preventability was determined by reviewers rather than having clearly defined conditions. As a performance indicator, a standardised set of conditions for what is determined to be preventable is required to be defined. A proposed framework is shown below in Figure 3.4. This image has three major components, the final indicator definition being on the left. By combining this model with the stakeholder infrastructure requirements, it's possible to develop an indicator that is evidence based and usable within NSW Health.

3.5 Creating a potentially preventable hospital readmissions indicator

As shown in Figure 3.3, different levels of readmissions can be visualised as subsets of one another. We overlayed the readmission levels in Figure 3.3 with two common 'Filters', which further subdivide the potentially preventable readmission subset, the first only selects patients over 65 years of age, similar to the United States' Medicare All Cause Unplanned Hospital Readmission measure [27] and the second selects only the hospital factors listed in Table 3.3. This causes certain readmissions to be excluded as shown in Figure 3.2, and there will be readmissions of interest, especially as a subset of planned readmission. Previous studies involving root cause and fault tree analysis have shown factors which lead to potentially preventable readmissions [11, 22], however these were not deemed within the scope of the indicator by NSW Health stakeholders. The majority of factors leading to readmission were identified as 'disease related', 'patient factors' or 'staff coordination and monitoring factors' [11].

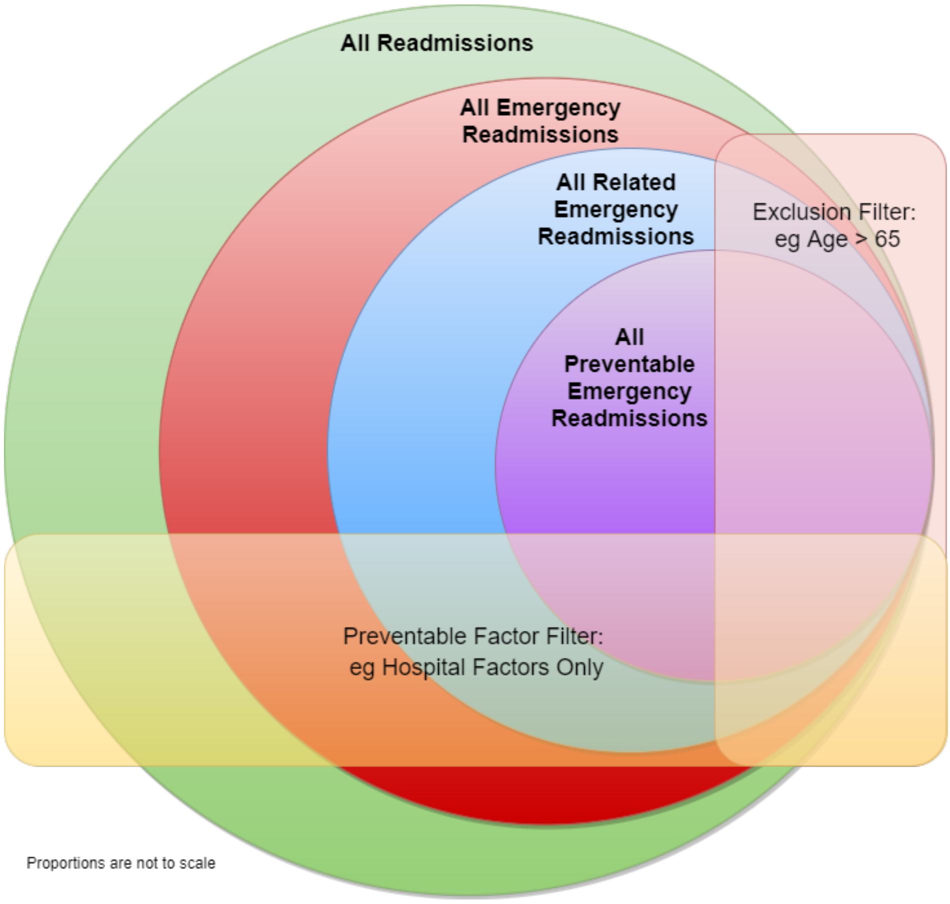


FIGURE 3.3: Hierarchical structure of readmissions as subsets.

When forming the performance indicator we categorised factors and region of geographical interest into four major constraints. Preventable Causes, Exclusion Filters, Layer and Duration. Preventable causes is divided up into four sub-categories, Hospital factors, Transition Factors, Community-Care factors, and Patient Factors. Each sub-category can have certain attributes assigned to it, such as a preventable adverse event during the index admission is a Hospital factor, while communication between hospital and community-care staff would be a Transition factor. This constraint is what separates an Unplanned Readmissions measure from a Potentially Preventable Readmission measure. The next three constraints are common to All Readmissions, Unplanned Readmissions and Preventable Readmissions.The Exclusions constraint deals with what is included in a dataset. It includes Patient Factors, which identifies whether an individual patient's circumstances exclude them from analysis. For example, when a patient leaves against medical advice, it is considered that the hospital could not change the outcome, additionally patients who die during the period being examined are also generally excluded from readmission analysis, as deceased patients are unable to be readmitted. Population factors includes excluding patients from analysis due to a range of causes. This type of exclusion is demonstrated in the CMS All-cause Unplanned Readmission measure, where it excludes patients under the age of 65 and any whose index admission was not one of five conditions. The final exclusion sub-category is data quality, which covers patient records being removed for causes such as missing data, errors in coding, or events such as transfers which may be coded as a discharge, when the record would be covered by another hospital.

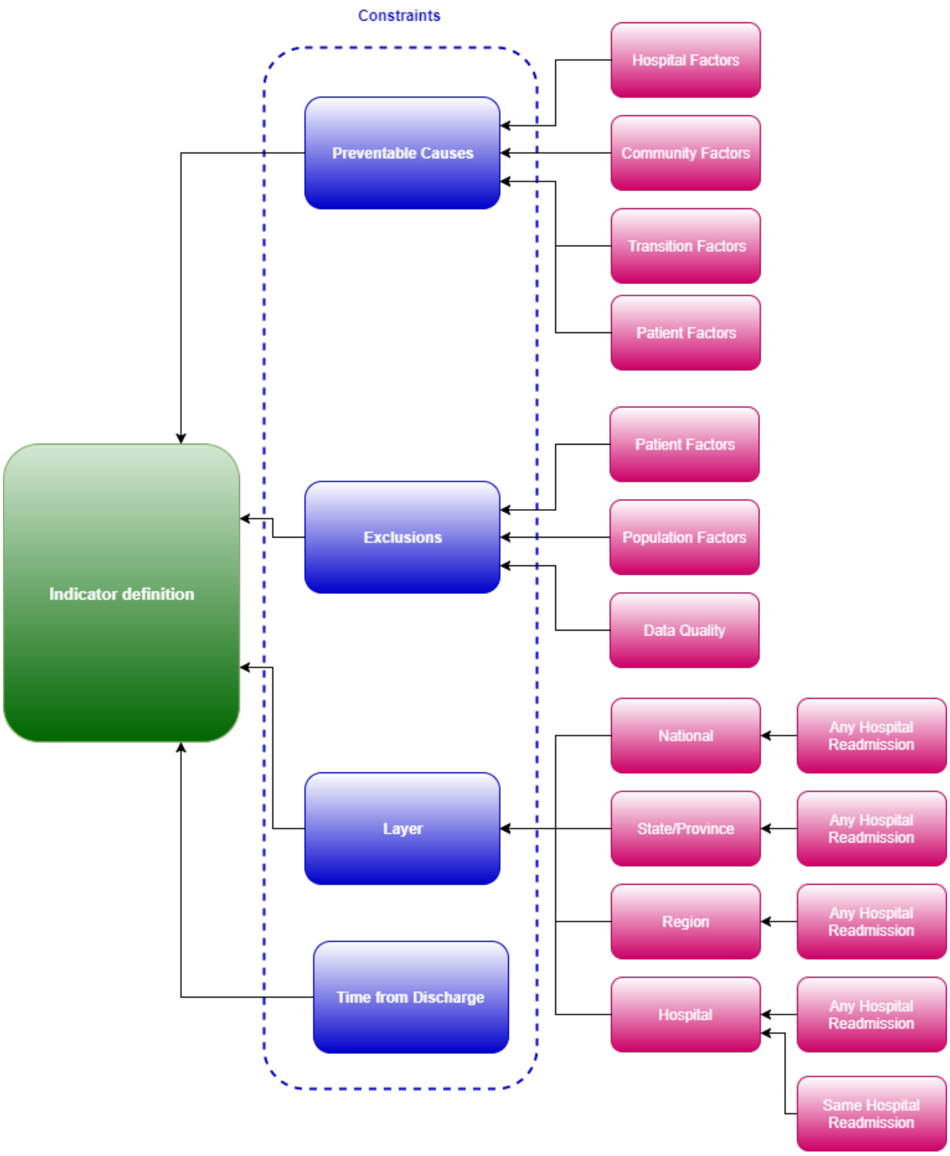


FIGURE 3.4: Breakdown of a Definition Model

The third constraint is the "Layer" or level at which the data is being analysed. National rates will consider all hospitals within the nation to determine the overall performance, while a hospital administrator seeking to improve their hospital performance will focus upon only their singular hospital performance. The hospital layer is unique in that it has two sub-layers within it, which is a consideration of data availability. There is a substantial increase in readmission rates when you consider patients who are readmitted to any hospital rather than only the hospital that performed the index admission [33, 62].

Wherever possible, any hospital readmission should be used as it is a more accurate representation of patient behaviour. The fourth and final constraint is the duration. The most common duration currently used in measurement is thirty days after discharge. However there is evidence to suggest that for certain conditions that other durations such as ninety days after discharge should be used [57]. From the literature, the current standard is a thirty days and captures roughly fifty percent of all readmissions [24].

This leads to defining the Potentially Preventable Hospital Readmission performance indicator. It is proposed that it should have the following structure: Potentially Preventable Hospital Readmissions where action taken or changed *during/by Hospital/Transition/Community/Patient* measuring performance of hospitals *[in area:region/state/nation]* within *duration* days of *[list of non-excluded]* patients.

Chapter 4

Implementation and Results

4.1 Introduction

In this chapter we take the Indicator and Definition developed in Chapter 2 and convert it into a Data Definition for use in New South Wales. The Data Definition was operationalised in Python and validated to ensure its suitability for use within the NSW Ministry of Health and the NSW healthcare system. In order to conduct this validation, we made use of an audit performed by the Northern NSW Local Health District (NNSWLHD) on unplanned hospital readmission over a two month period. As this audit was pre-existing, the geographical area of this implementation, as described in Section 4.3.2, was limited to hospitals in the NNSWLHD rather than the entire state.

A hospital readmission was considered potentially preventable if "action taken or changed by the hospital during a patient stay or transition to community care could have potentially prevented the readmission in the NNSWLHD within 28 days of discharge". The presence of transplant, chemotherapy, radiotherapy and cancer related conditions in the index admission or in the readmission was not considered preventable as cancer patients and patients undergoing transplants are complex patients likely to return to hospital unexpectedly for further treatment. Patients with readmissions due to acute trauma as the cause of readmission are excluded by this definition as the cause would not have been preventable by the hospital. As this indicator is a subset of unplanned readmissions as elaborated upon in Section 3.5, in particular Figures 3.2 and 3.3, planned readmissions such as dialysis or follow-up appointments to the hospital are also excluded. Maternity and neonatal readmissions were also excluded from being considered preventable. Infants are more fragile than adults and hospital policies often discourage risking negative patient outcomes due to not readmitting a neonatal patient, which leads to a lower threshold for admission. As we have learned from Chapter 3, these exclusions are common in other studies and definitions.

Our definition of PPR was implemented in Python using a modified version of SQLape [35] as described in Section 4.4.2. To differentiate between the two, we call this tool pyLape. SQLape was originally developed in Switzerland by researchers associated with the société à responsabilité limitée [35, 65]. SQLape was chosen because it has similar inclusion and exclusion criteria as our proposed definition and it has been previously validated in two different healthcare systems [35, 66].

The overall potentially preventable readmission rate was determined to be 16.7 percent of unplanned readmissions in the NNSWLHD for the duration of the audit. The audit included readmissions deemed preventable by factors other than than hospital and transition to community care such as patient, community care and 'other' factors, the latter of which included readmissions deemed preventable, but had no specific factor given. However, the proposed indicator only measures hospital and transitional factors which had a rate of 3.43 percent of readmissions as determined by the audit, the performance of pyLape in identifying potentially preventable hospital readmissions was good, although transitional factors had poor performance. Moving to a more encompassing indicator which measures the other factors is not possible with the available hospital information. To implement a measure on a statewide level, which includes community and patient factors (such as access to community care, patient living conditions and patient preferences) outside hospital would require additional relevant information to be available at the patient level.

4.2 Converting the Definition to a Data Definition

To convert the definition of the performance indicator proposed in Section 3.5 to a data definition, examination of its proposed use and available data must be conducted. In this thesis, a pilot implementation of the proposed data definition (pyLape, Appendix B) took place using hospital administrative data from the NNSWLHD. As this is a linked dataset, it is possible to track unplanned patient readmissions to any hospital within NSW.

As mentioned in the introduction to this chapter, the indicator operationalised in this thesis is: Potentially Preventable Hospital Readmissions where action taken or changed by the Hospital during a patient stay or transition to community care could have potentially prevented the readmission in the NNSWLHD within 28 days of discharge for all patients. Australian Refined Diagnosis Related Groups (AR-DRGs) and ICD-10-AM codes were the main identifiers of patient conditions and comorbidities. A Readmission and its associated index admission which related to maternity, neonatal care, cancer, transplants, acure unrelated trauma and dialysis were not considered preventable. Patient ethnicity, including Aboriginal and Torres Strait Islander status is not included in the data. Full details of these data can be found below in Sections 4.3.1, 4.3.2 and 4.3.3.

4.3 Data sets

The NNSWLHD UHR 2014 Audit was conducted during the months of June and July. This dataset was linked to the NSW Admitted Patient Data Collection (APDC) by the Centre for Health Record Linkage (CHeReL) [67]. Hospital admissions one month before and one month after the study period (May->August) were also included in the linked dataset to capture index admissions and follow-up care. Access to the datasets used in this research were provided by NSW Health, with the Admitted Patient data set accessible through NSW Health's SAPHaRI (Secure Analytics for Population Health Research and Intelligence) environment. SAPHaRI is a secure data storage containing the linked APEDDR (Admitted Patient, Emergency Department, Death Registry) datasets. The platform also allows for other datasets to be imported and stored securely. The Northern New South Wales Audit dataset, used for validation purposes was also imported into SAPHaRI for secure storage and access. Ethical approval for the project and use of patient data was granted by the NSW Population & Health Services Research Ethics Committee [68].

The first part of the linked dataset was created from the audit tool as shown in Appendix A. The audit dataset included the principal diagnosis, recorded as the Diagnosis Related Group (DRG) code for both index and return admissions, potential relationship between admissions, whether the readmission category was correct (data integrity), patient functional status, patient's disposition after previous discharge, whether the clinician believed that a patient was likely to die in the next 12 months, whether they were likely to go into residential care in the next 12 months, the Ontario HARP score for the previous admission, whether there were any preventable factors relevant to the readmission and whether the clinician believed that the readmission was preventable. It also included the hospital the patient was readmitted to and the patient's date of birth which was used for age and linkage purposes.

4.3.1 Admitted Patient dataset

The Admitted Patient dataset consisted of all hospital separations in the NNSWLHD between May to August 2014 as recorded in the NSW APDC collection. The APDC contains basic patient information such as age, gender, insurance status and marital status, as well as hospital administrative data such as source of referral, mode of separation, admission and separation dates and discharge codes. Each patient record contains diagnosis and procedure codes in ICD-10-AM format. Each diagnostic code has an associated condition onset code to inform analysts of whether the patient had the condition at the time of admission or whether it was developed during the hospital stay. A full variable list of the APDC can be found at the CHeReL website [67]. The total number of unplanned readmissions found in the data linkage process that matched to the NNSWLHD audit was 460.

4.3.2 Northern NSW Unplanned Hospital Readmission Audit Dataset

The NNSWLHD UHR 2014 Audit was conducted as a chart review by clinicians on all readmissions to any hospital in the NNSWLHD during the months of June and July. The main purpose of the UHR dataset was to identify preventable factors which was a cause leading to the readmission. This dataset included admission and discharge dates for both the index and return admissions, allowing for identification and linkage with admissions in the APDC. The total number of patient records included that contained a potentially preventable factor as determined by the audit was 109.

The audit dataset included the principal diagnoses, recorded as the Diagnosis Related Group (DRG) code for both the index and return admissions. Whether the clinician believed that the two admissions were potentially related to one another. The clinician checked whether the readmission category was correct to ensure data integrity. The functional status of the patient and where they had previously discharged was also captured as free text. The end of life, aged care and discharge location were out of scope of this thesis so were not included in the final dataset. The audit also included five categories of preventable factors that could lead to a potentially preventable readmission: hospital, transition to community care, community care, patient and other factors. After the preventable factors, a column that had either a true or false value to summarise whether preventable factors were present. An additional column contained the clinician's opinion of whether the factors present led to the readmission or not, this column contained one of the six following values: Strongly agree, Agree, Unsure, Disagree, Strongly disagree, and Unknown. This last column allowed for a clinician's judgement to be expressed and was used to provide more in depth analysis of the performance of the algorithm.

4.3.3 Final linked dataset

To properly utilise the SQLape algorithm, the diagnosis codes, procedure codes, condition onset codes, admission and discharge dates were extracted from the APDC dataset and linked to the UHR audit data. The discharge code for all patients was also included to identify which patients discharged at own risk (roughly equivalent to the discharged against medical advice in other datasets) to see how their inclusion or exclusion influenced the output.

4.3.3.1 Data cleaning and recoding

The linked dataset contained instances of the index admission being linked to multiple readmissions in the NNSWLHD UHR dataset. Manual analysis of these records (<10) showed that they were transfers from one hospital to another in the readmission and had not been joined in the original audit. In this final dataset used for this project, these multiple readmissions were combined into a single admission record for analysis in pyLape.

There were two columns in the PPR subset of the NNSWLHD UHR audit which stated preventability. The first column contained True or False values of whether a preventable factor existed, while the second was whether the clinician agreed that the preventable factor led to the readmission as described in Section 4.3.2. Where the clinician disagreed, the readmission was not included as a PPHR, but was not removed from the dataset for analysis.

As SQLape is an international algorithm, it utilises international ICD-10 diagnosis codes and ICD-9-CM procedure codes. To make the dataset compatible with SQLape codes the ICD-10-AM codes were converted into their international equivalents. The diagnosis codes were converted from ICD-10-AM 2014 to ICD-10-AM 2016 and then to ICD-10 (International/WHO) with a mapping supplied by NSW Health. No direct map from ICD-10-AM to ICD-9-CM exists for procedure codes. To convert each code, they were first converted edition by edition from the 2014 ICD-10-AM edition to the first ICD-10-AM edition in 1998. Utilising a map from ICD-10-AM First edition to ICD-9-CM 1998 edition, they were converted to ICD-9-CM. Once converted to ICD-9-CM a map of changes to the ICD-9-CM standard from 1998 to 2016 was used to convert the procedure codes to the current SQLape codes.

4.4 Algorithm overview

4.4.1 SQLape

SQLape is an algorithm developed to identify potentially preventable hospital readmissions from hospital administrative data. It has been successfully validated with the Chart Review process in Switzerland and the United States [35, 66]. SQLape makes the assumption that a readmission for a clinically related diagnosis is potentially preventable but uses additional information from administrative hospital data to minimise the difference between a clinician's training and experience and the algorithm [63].

The algorithm has been rewritten in python to interface with the NSW Health SAPHaRI data warehouse and adapted to the variables available in the Australian dataset. The modifications are detailed in section 4.4.2. To minimise confusion the modified algorithm is referred to as pyLape.

SQLape is a multistep algorithm, checking for the existence of diagnoses and procedures that are commonly associated with non-preventable readmissions, before identifying potentially preventable causes of readmission. The steps followed by SQLape are illustrated in Figure 4.1.

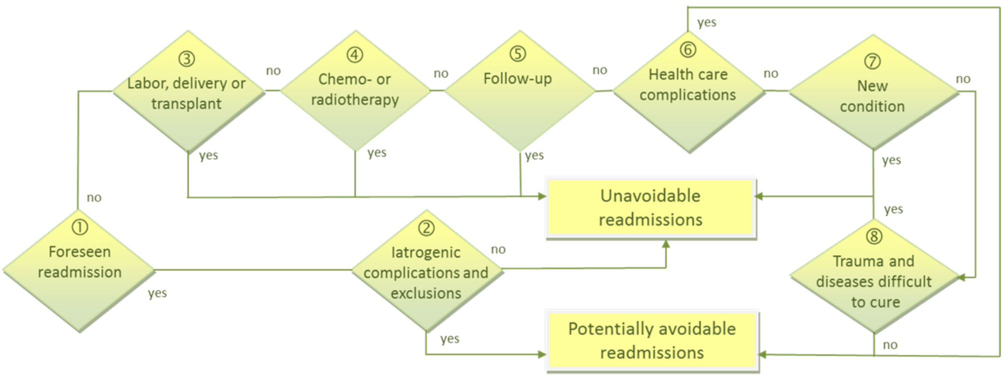


Figure 4.1: SQLape Algorithm Flowchart [65]

- Step 1: Identify whether the readmission was planned or unplanned. SQLape conducts this step using a list of predetermined procedures and diagnoses, examples of this would include regular procedures such as dialysis. In the datasets detailed earlier in this chapter, these readmissions were excluded and thus were not available to fully test this step. If a readmission was determined to be unplanned, go to Step 3.

- Step 2: Check for complications and certain exclusions within the planned readmissions, which even though they fit the criteria of being planned, the records indicate that there was a preventable complication that had to be addressed in the readmission. This is determined by a specific list of diagnoses and procedures that were considered preventable when relating to a planned readmission, an example being a complication of a dialysis patient excluded in Step 1 that had to be treated in a return admission.

- Steps 3 & 4: Exclude readmissions following the exclusion criteria listed in section 1.1.1: readmissions due to transplants, maternity, chemotherapy or radiotherapy and if so, categorising the readmission as unavoidable. If not excluded proceed to Step 5.

- Step 5: Identify follow-up visits and rehabilitation visits that are required for proper treatment but might not be planned at the time of discharge. This was done by checking the patient diagnosis and procedure codes against a list of codes that are specific to follow-up and rehabilition admissions. If not excluded proceed to Step 6.

- Step 6: Checks if there was a complication that is being dealt with in the return admission, either with the disease or a surgical procedure. This is similar to the method used in Step 2, however the list is larger, including a greater range of complications that are associated with unplanned readmissions that were potentially preventable. If a particular type of complication exists, then it is categorised as preventable, otherwise it progresses to Step 7.

- Step 7: Check if there is a relationship in the systems that were being treated in the index admission and the primary diagnosis of the readmission, where there is no relationship the readmission was considered non-preventable. If there is a relationship between the damaged systems, proceed to Step 8. SQLape utilises a proprietary grouping algorithm to determine the relationship of damaged systems, which matches systems that were damaged in the index admission and if the main cause of readmission was damaged in the previous admission.

- Step 8: Checks if the readmission is due to trauma or other diseases that have a high rate of readmission without any issues due to treatment that may negatively affect the reported rate. If the readmission isn't due to trauma or disease progression, then they are categorised as preventable.

Each of these steps matches up certain aspects of the definition. Step one isolates out patients that should have been flagged as planned, while step two are tracked as separate preventable readmissions. Steps three and four process the exclusions explained in section 4.1. Step five removes other procedurally unavoidable readmissions. Step six identifies hospital actions that should not have occurred in the index admission that have led to readmission, while steps seven and eight determine whether the nature of the readmission condition is related and preventable.

4.4.2 How SQLape was modified for Australian Data

The complete pyLape algorithm is shown in Appendix B. The SQLape algorithm was developed in Switzerland for use in the Swiss healthcare system [35]. A side effect of this is that the datasets available to Australian researchers do not include all of the same information that is required to run an unchanged SQLape algorithm. Many of the steps described by Halfon et. al. require the knowledge of whether diagnoses or procedures occurred within the first 48 hours of readmission [35], the only dates available in the Australian dataset are admission and discharge dates. The modification made in this instance was to include all diagnosis and procedure codes during the readmission rather than approximating a number of codes to be included.

4.4.2.1 ICD-10-AM specific codes added to pyLape

In consultation with clinicians and members of NSW Health, it was noted that the codes used in Australia for surgical complications were different to the international ICD-10 and ICD-9-CM codes. The following codes were added into the variable lists used in pyLape to determine preventability: T83.8, T84.8, T88.9 all of which are codes frequently used in Australia for complications or adverse events.

In step 5, the ICD-10-AM rehabilitation procedure code was added to the list of rehabilitation codes as it was not included within SQLape's variable list. SQLape uses the ICD-10 (international) diagnosis code 'Z50', while New South Wales coding staff use the procedure code for rehabilitation '95550-03', which converts to '93.39' in ICD-9-CM.

4.4.2.2 Damaged systems grouping algorithm

Utilised within the latest version of SQLape is a proprietary grouping algorithm that determines the system(s) that were damaged at the time of the index admission. To approximate this grouping system, two methods were tested. The first was matching via AR-DRG between index and return admissions. This is a pre-calculated and casemix weighted classification that was developed for Australia. Matching by Disease Related

Group potentially excludes related readmissions that may not have been included in the final AR-DRG, but have a direct effect on readmission. The second method is via ICD coding based on categorisation. For example, where a procedure code in the range of 30.01-34.99 (ICD-9-CM, Operations on the Respiratory System) exists in the index admission, any procedure in the same range, or a diagnosis code in the J00-J99 range (ICD-10, Diseases of the Respiratory System) during the return admission would be considered of the same patient 'system' even if there is not a direct match.

As the SQLape grouping algorithm is proprietary, it is unknown how effective it would be upon Australian data. It is expected that refinements to the grouping algorithm will improve this step of the pyLape algorithm.

4.4.2.3 Condition codes replacing the forty-eight hour duration

In the original SQLape algorithm, certain sections compared diagnosis and procedure codes against the time with which they occurred. If they were less than forty eight hours, they were included, otherwise they were not considered to be a condition relating to readmission causes. The APDC dataset does not include timestamped data for individual codes, instead it provides a code for whether or not the diagnosis was present upon presentation or whether it developed during the hospital stay.

4.4.2.4 Post-algorithm analysis labelling

In addition to the python implementation of SQLape, which determines whether a readmission was preventable or not, each step of the algorithm was labelled in the output to allow for further analysis, to see the effect of how effective each part of the algorithm was. This also allowed for determining if patients discharging at own risk or being treated for mental health conditions in either admission had an effect upon the output.

4.4.2.5 Change of Step 7 to non-preventable

The step of the pyLape algorithm that caused the most False Positives was Step 7 in Figure 4.1. This step determined whether a previously damaged system was the main cause of readmission. It is also the step that utilises the proprietary algorithm in SQLape that was implemented differently in pyLape as described in Section 4.4.2.2. As this part of pyLape is potentially substantially different to SQLape, the results of that step alone were reclassified as not preventable in pyLape, the results of this change are shown in Table 4.2 in Section 4.5.1. Other attempts, including using Australia Diagnosis Related

Groups (AR-DRG), on both an individual level and the category the AR-DRG belong to, to attempt to identify whether the patient returned with a new condition or not did not substantially increase performance.

Prior to disabling step 7, the specificity of pyLape was extraordinarily low at 0.039. The Sensitivity was high at 0.961, however this was due to 96 percent of all readmissions being identified as preventable, with 83 percent of all positives being a type I error. As no study in the literature nor the UHR audit contained results similar to this step of the algorithm, there is no evidence that it was correct. Thus the flag was set to non-preventable for this step, however the label of the step was maintained as specified in Section 4.4.2.4 so that it could still be identified for manual investigation.

4.5 Admission and readmission rates

Table 4.1 shows readmission rates across the hierarchical levels of the definition: unplanned readmissions, all potentially preventable readmissions, and potentially preventable readmissions associated with each of the individual factors examined in the audit. All-cause readmission was not available because the linked dataset only included the unplanned readmissions. The numbers for All Admissions was drawn separately from the summarised records for the region, but it was not possible to count total readmissions as the patient linkage was based upon only patients with an unplanned readmissions. The rate of potentially preventable readmission was 16.7 percent, which matches within the error for other estimates of the preventable rate in Australia as discussed in Chapters 2 and 3. The number of potentially preventable readmissions in the table (listed as PPR All Causes due to space limitations) is 77 rather than 109 due to the following conditions: removal of duplicates, there were also multiple cases of two different readmissions with the same dates matched up to the same index admission with the same category of preventable factor listed for the same patient; removal of transfers between hospitals, caused by the audit not having access to properly linked records which was available to this research; and removal of patient cases where a clinician recorded that they disagreed with the preventable factor being the cause for readmission, for example where a preventable factor was identified, but in the clinician's opinion the readmission was not preventable due to other factors in the chart review.

TABLE 4.1: Changes in readmission rate depending on level of focus

Readmission Level	No. of Pts.	Read Rate	Total Admit Rate
All Admissions	5830	–	100%
Unplanned Readmissions	460	100%	7.6%
PPR All Causes	77	16.7%	1.32%
PPR Hospital Factors	14	3.00%	0.24%
PPR Transition Factors	2	0.43%	0.03%
PPR Patient Factors	21	4.57%	0.36%
PPR Community Factors	3	0.65%	0.06%
PPR Other Factors	43	9.35%	0.74%

4.5.1 Performance of pyLape for the identification of all-cause unplanned PPR

The first comparison of pyLape vs audit was done for all-factors of potentially preventable readmissions. The confusion matrix shown in Table 4.2 compares the output of pyLape against the audit's all-cause potentially preventable readmission after converting the potentially related step to be classified as not preventable as explained in Section 4.4.2.5. The number of True Positives was 8, but the number of False Negative was the majority of preventable factors identified by the audit at 69. Therefore, Sensitivity was quite low (0.104). The Specificity is high at 0.9896. This result is not surprising since pyLape was expected to perform poorly across some factors. The following sections will examine each factor in detail.

TABLE 4.2: UHR Audit All Cause vs pyLape All Cause

UHR Audit All Cause (columns); **pyLape All Cause** (rows)

	p	**n**	**total**
p′	TP 8	FP 4	P′ = 12
n′	FN 69	TN 379	N′ = 448
total	P = 77	N = 383	

Sensitivity = 0.1039 Specificity = 0.9896

Table 4.3 shows the causes leading to True Positives, False Positives and False Negatives in the pyLape results.The False Positive category was associated with Readmission

Procedure, Surgical Complications, Cardiac Complications and Medication (the Medication category can include drug related adverse events, or given the wrong drug, or the wrong dose). The latter two categories were identified by the "Hospital Acquired Complications" step in the algorithm as specified by the Australian Commission on Safety and Quality in Health Care. These standards were registered in 2015, while the audit occurred in 2014. The Surgical Complications True Positive to False Positive rate shows promising signs, as it is part of the check for complications step in pyLape, which falls under the Hospital Factors section.

Table 4.3: pyLape Identified Causes for All Causes including Potentially Related as Preventable

pyLape Identified Causes	True Pos	False Pos	False Neg
Complications - Surgical	7	2	0
Healthcare Infection	1	0	0
Cardiac Complications	0	1	0
Medication	0	1	0
Potentially Related	0	0	63
Oncology	0	0	1
Patient Decision	0	0	2
Readmission Procedure	0	0	2
Follow Up	0	0	1

The False Negative column has the largest numbers in it, due to containing the Potentially Related category. Potentially related was moved here as discussed above. False Negative also included a patient identified as an oncology patient and two patients that left against medical advice, both of which are common exclusions in preventability studies. With this modification to the data output, due to the massive distortion of the data caused by the Potentially Related category, the performance of pyLape against individual readmission factors can be assessed.

4.5.2 Performance of pyLape for the identification of unplanned PPR related to hospital factors

Unplanned PPR are considered related to hospital factors where there are actions that could potentially have been performed differently in the hospital to prevent a readmission. Most of these actions are classified in the data as complications. As shown in the confusion matrix (Table 4.4) the sensitivity for the identification of these readmissions is acceptable (0.6) and specificity remains high (0.9867). This is a substantially different performance from the All Cause results in Table 4.2.

Table 4.4: UHR Audit Hospital Factors vs pyLape All Cause

		UHR Audit Hospital Factors		
		p	**n**	**total**
pyLape All Cause	**p′**	TP 6	FP 6	P′ = 12
	n′	FN 4	TN 444	N′ = 448
	total	P = 10	N = 450	

Sensitivity = 0.6 Specificity = 0.9867

Breaking down the identified causes of the hospital factors in Table 4.5, the False Positive column is the most interesting. The number of Surgical Complications that are hospital factors differs to those listed in Table 4.3, along with the Healthcare Infection being classified as a False Positive which was identified as preventable previously. Examining the records for the False Positive Surgical Complication and the Healthcare Infection, both had no factor given by the auditor. They were classified as having a preventable factor, but no further clarification was given. As discussed in Section 4.5.1, the Cardiac Complications and Medication causes were deemed preventable by an algorithm that was developed after the audit was conducted. In examining the individual patient records, the patients were not identified with a preventable factor that the clinician determined to not have been the cause of readmission. We have assumed here that the selected hospital acquired complications are in fact preventable. In the interest of more up to date accuracy, these four False Positives should be moved to the True Positive column. The reason why clinicians may have missed these preventable factors during the audit is outside the scope of this thesis.

Table 4.5: pyLape Identified Causes for Hospital Factors

pyLape Identified Causes	True Pos	False Pos	False Neg
Complications - Surgical	6	3	0
Healthcare Infection	0	1	0
Cardiac Complications	0	1	0
Medication	0	1	0
Potentially Related	0	0	4

With the number of False Negatives being so low, it is possible to examine them in detail, to see what the auditors wrote about the individuals. The following list gives the preventable causes as given in the audit:

- Patient 1:
  - Missed or inappropriate treatment
  - Patient discharged on antibiotics proven to be resistance to causative organism
- Patient 2:
  - Missed or inaccurate diagnosis
  - Progression of Disease
- Patient 3:
  - Missed or inappropriate treatment
- Patient 4:
  - Missed or inaccurate diagnosis
  - Should have had U/S of wound on representation after 5 weeks

As can be seen from the list, all the False Negatives have a missed or inaccurate diagnosis or treatment in common. These appear to be difficult to detect from the ICD-10-AM codes supplied in the dataset. Since Patients 1, 2 and 4 give further information on the preventable factors, each will be analysed in more depth. Examining Patient 1, the supply of the wrong antibiotic drugs was a hospital (in this case staff) error that should not have happened. Unfortunately for pyLape no codes were listed in the hospital admin data that allow an algorithm to determine this cause. Patient 2 was a misdiagnosis and returned due to the original disease progressing, needing further/correct treatment. Patient 4 is interesting when looking at the notes and comparing them to the admission dates. The index and readmission in the dataset are less than three days apart, a very quick return to hospital, versus the five weeks stated in the notes. It appears that the original cause of the index admission was a previous hospital visit five weeks prior (a week or less outside the duration of the return period for the study depending on the exact dates) which still had a wound upon presentation. According to the notes, in the listed index admission, an ultrasound should have been conducted to find the reason the wound wasn't healing correctly and then to proceed with correct treatment.

After analysing the False Positives and the False Negatives, an adjusted Hospital Factors confusion matrix was made, moving the Surgical Complication with an unknown cause to become a True Positive. In the following table we have assumed the causes identified by the more modern hospital acquired complications to be True Positives while leaving the four False Negatives listed individually above as shown in Table 4.6.

TABLE 4.6: Adjusted UHR Audit Hospital Factors vs pyLape All Cause

pyLape All Cause		UHR Audit Hospital Factors **p**	UHR Audit Hospital Factors **n**	**total**
	p′	TP 10	FP 2	P′ = 12
	n′	FN 4	TN 444	N′ = 448
	total	P = 14	N = 446	

Sensitivity = 0.7143 Specificity = 0.9955

The adjusted Hospital Factors pyLape detection has a Specificity of 0.9955 and Sensitivity of 0.7143 which is a very good performance, and leads us to assess that where the data is present it is possible to determine potential preventability. These numbers must be taken with caution. Although the surgical complications without a listed reason in the audit, can be reasonably expected to be potentially preventable, other complications such as Healthcare Infection, Cardiac Complications and Medication-related readmissions should be taken with caution in the absence of further information.

Where there is no ICD-10-AM code used to state that an incorrect diagnosis or procedure recorded this method of determining preventability doesn't work, however these were a minority of hospital factors. Combining the True Positive and False Negative numbers together gives us a overall potentially preventable readmission rate of 3.00 percent for Hospital Factors alone. This a significant contributor to the estimated rate of potentially preventable readmissions, which has been previously estimated as 16.7 percent. In following sections, the other factors, such as Transitional Factors and Patient Factors are examined and their contribution to the overall potentially preventable readmission indicator is considered.

4.5.3 Performance of pyLape for the identification of unplanned PPR related to transition factors

The second factor that was included in the definition given earlier in Section 4.1 was Transition Factors, which are potentially preventable events or causes that occur during the transition from hospital care into the community. Table 4.7 shows the confusion matrix. This had a low occurrence within NNSWLHD's audit, where only two cases were identified as having a transitional factor. Neither was detected by pyLape. The Sensitivity of zero (0.0) in this instance gives us the ability to state that pyLape in its current form is unable to determine transition factors with any reliability. The exact breakdown of the False Positives is discussed below.

TABLE 4.7: UHR Audit Transition Factors vs pyLape All Cause

		UHR Audit Transition Factors		
		p	**n**	**total**
pyLape All Cause	**p′**	TP 0	FP 12	$P' = 12$
	n′	FN 2	TN 446	$N' = 448$
	total	$P = 2$	$N = 458$	

Sensitivity = 0.0 Specificity = 0.9738

Table 4.8 shows the breakdown of False Positives (12), False Negatives (2) and True Positives (none). Starting with False Positives within the all cause of pyLape, all of the 12 False Positives were identified as Hospital Factors in Section 4.5.2. The two False Negatives were in the potentially related category which due to poor specificity had to be excluded from being considered potentially preventable in pyLape.

Considering that the entirety of false positives were identified as hospital factors it is possible to state that the current implementation pyLape has no ability to discern the presence of transition factors. This leads us into the following factors, patient and community care, which have a similar sensitivity to transitional factors.

Table 4.8: pyLape Identified Causes for Transition Factors

pyLape Identified Causes	True Pos	False Pos	False Neg
Complications - Surgical	0	9	0
Healthcare Infection	0	1	0
Cardiac Complications	0	1	0
Medication	0	1	0
Potentially Related	0	0	2

4.5.4 Performance of pyLape for the identification of unplanned PPR related to patient factors

The patient factors identified in the audit were a large proportion of the identified potentially preventable factors. It must be noted that the numbers in Tables 4.9 and 4.10 for False Negatives don't match. This is because in Table 4.9 the patients where the auditor determined that the preventable factor did not lead to readmission were excluded. This was described in depth in Section 4.3.2. Only including the cases where the clinician agreed (or their belief was unknown) did not affect the numbers in previous sections.

Table 4.9: Patient Factors where Clinician Agrees vs pyLape All Cause

Patient Factors where Clinician Agrees

pyLape All Cause		**p**	**n**	**total**
	p′	TP 0	FP 12	P′ = 12
	n′	FN 21	TN 427	N′ = 448
	total	P = 21	N = 439	

Sensitivity = 0.0 Specificity = 0.9727

Patient factors is the first factor that we're examining that is not included in the definition given at the beginning of the chapter. However patient factors along with the following sections were included in the audit, so analysis on how pyLape performs is being conducted upon them.

Table 4.9 shows that there were twenty one False Negatives where the clinician's opinion on the preventability of readmission was that they either Agreed, were Unsure or their opinion was unknown (no response recorded in the dataset). This was the second largest category identified in the audit, however due to the way hospital admin data is recorded, with only diagnoses and procedures conducted within the hospital stored as ICD-10-AM codes without any notes on patient factors which may be included in a patient's chart. It was not expected that the information required to identify patient factors would be included in the linked dataset.

Table 4.10: pyLape Identified Causes for Patient Factors

pyLape Identified Causes	**True Pos**	**False Pos**	**False Neg**
Complications - Surgical	0	9	0
Healthcare Infection	0	1	0
Cardiac Complications	0	1	0
Medication	0	1	0
Potentially Related	0	0	18
Oncology	0	0	1
Patient Decision	0	0	2

Looking at the False Positives in Table 4.10 they are the same as the transitional factors in Section 4.5.3, with the majority being associated with hospital factors. The False Negatives column is more interesting, with two Patient Decisions (where a patient left against medical advice) identified. Another was removed due to Oncology. All three of these cases are often removed in automated systems, due to the complex nature of patients acting contrary to medical advice and the difficulties involved with the cancer treatments they are excluded from the dataset prior to the algorithm running further. The 18 other False Negatives (including patients where the clinician determined that the preventable factor did not lead to readmission) were all identified by pyLape as Potentially Related. It is possible that an improved grouping algorithm could have significantly improved results in this area, but would require further testing.

As this is such a large portion of the identified potentially preventable readmissions making up 4.57 percent of all unplanned readmissions, between patient factors and hospital factors they make up the vast majority of potentially preventable readmissions that have a listed cause. Having the data to autonomously identify patients readmitted to preventable patient factors would lead to substantial improvements in measuring the potentially preventable readmission indicator.

4.5.5 Performance of pyLape for the identification of unplanned PPR related to community care factors

The community care factor accounts for actions that could have been done differently in the community (including healthcare professionals outside the hospital, such as family doctors or hospital in the home nurses) that would have prevented a readmission to hospital, much like the other causes. Table 4.11 shows that as there were only three identified False Negatives, a manual examination of each patient in the audit was conducted. Two were also in the Patient Factors category. One was listed as patient non-compliance due to having inadequate transport to be able to attend appointments with healthcare systems in the community, and the other had an impaired mental state which caused problems with the patient's medication management. The third community factor was also due to medication management, with no further details supplied.

TABLE 4.11: UHR Audit Community Factors vs pyLape All Cause

pyLape All Cause	UHR Audit Community Factors: **p**	**n**	**total**
p′	TP 0	FP 12	P′ = 12
n′	FN 3	TN 445	N′ = 448
total	P = 3	N = 457	

Sensitivity = 0.0 Specificity = 0.9737

The community care factors identified involved either problems with medication management or the ability to attend appointments. The data required to improve measurement of this would involve records of fulfilling scripts at a pharmacy, or dates for attending or missing healthcare appointments. Community care factors make up 0.65 percent of all unplanned readmissions.

4.5.6 Performance of pyLape for the identification of unplanned PPR related to other and unidentified factors

The final category of factors to be examined is the "Other" category. By far the largest, the Other category also includes those potentially preventable factors that were uncategorised, or unlabelled in the audit. It was also used as a category to elaborate upon other factors that were identified, such as the False Negatives in the earlier section discussing Hospital Factors, where it was listed as a missed or inaccurate treatment or diagnosis. Table 4.12 is the confusion matrix for the other factors where a clinician agreed versus the pyLape output, there were multiple cases where a clinician disagreed with the preventability, including one with the comment "Unable to determine cause of readmission", along with cases of transfers back and forth between hospitals for specialist procedures or chronic conditions. The same twenty pyLape positives as the other factors were found, however the one Surgical Complication from Hospital Factors appears here as a True Positive. The Sensitivity was very low at 0.0435 however the Specificity was high at 0.9758.

TABLE 4.12: UHR Audit Other Factors vs pyLape All Cause

pyLape All Cause	UHR Audit Other Factors: **p**	**n**	**total**
p′	TP 2	FP 10	P′ = 12
n′	FN 44	TN 404	N′ = 448
total	P = 46	N = 414	

Sensitivity = 0.0435 Specificity = 0.9758

In addition to being a category elaborating upon other factors, or identifying a preventable factor but disagreeing with the preventability of the readmission, a large number (32 of 43) of the other factors category had no identified cause or clinician opinion on whether the readmission was actually preventable. Many were categorised by pyLape in the Potentially Related category, so hopefully further development of that part of the algorithm will gather improved results. The 'other' category made up 9.35 percent of all unplanned readmissions, larger than all other categories combined. This could possibly be explained with the lack of information and classification of the causes that could be put into a future audit.

4.6 Summary of Results

In Section 4.5 we identified the rates of potentially preventable readmissions based upon the audit, along with breaking the overall rate down by the different factors involved. The indicator proposed in Chapter 2 was converted into a data definition in Section 4.2 which identified that the indicator of interest in this research project involved the hospital and transition to community care factors. The choice of limiting the indicator and by extension the data definition to hospital and transitional factors was due to the features of the dataset available, which did not include information about the patient from outside of the hospital. After describing the dataset and the quirks of Australian data compared to the datasets from the United States and Switzerland that SQLape had been used with prior, the changes that were made to SQLape to work with Australian data was explained.

These changes showed a good result for identifying hospital factors as shown in Section 4.5.2, with a very accurate Sensitivity for determining if there were complications during the previous admission and an excellent rate at not misclassifying False Positives in the adjusted set, there is substantial evidence that pyLape can be utilised to identify potentially preventable readmissions due to hospital factors. The results were not as impressive for the other factors, however when it came to Type I errors, pyLape had extremely good performance. Error ranges were not included as the NNSWLHD's audit had too few patients reviewed to provide reliable estimates.

Chapter 5

Conclusion

5.1 Summary of contributions

Over the course of this thesis, an examination of the current methods of measuring unplanned readmission in healthcare systems in Australia, the U.K. and U.S.A was conducted, providing an understanding of how current performance indicators work in practice and how they could be improved. This led us to propose a hierarchy of performance indicators which moves from the easiest to operationalise all-cause readmission, through all-cause unplanned readmission into the most challenging to operationalise potentially preventable readmission. This hierarchical aspect conceivably allows for smooth transitions from higher levels of the hierarchy where relevant data is available to lower, more relevant levels, as data availability and quality improve. In validating that it is possible to measure hospital factors leading to potentially preventable readmission, we have opened the way to creating a standardised, evidence-based indicator for use in the Australian healthcare system.

This thesis analysed the differences and similarities among performance indicators and proposed definitions of potentially preventable readmission. It discussed how patients and factors are excluded based on data availability as well as on the focus of the research being conducted. This led to proposing the use of filters such as healthcare layer (hospital, region, or national), patient inclusion/exclusion criteria(e.g. age), data quality inclusion/exclusion criteria (e.g. missing records), and preventability factors (e.g. hospital factors). Using these filters along with the hierarchical model allows for easy comparisons among proposed indicators and provides NSW Health with a platform for planning data gathering required for future improved performance indicators.

Substantial work went into customising SQLape to work with Australian datasets, due to differences in data recording, such as diagnosis and procedure classification codes, and the way data was timestamped. The largest change being the definition of new condition, which is proprietary. Nevertheless, pyLape's identification of hospital factors had high Sensitivity and Specificity. All the False Negative hospital factors were cases where there was a missed or inaccurate diagnosis or treatment in the index admission which would not be described by ICD-10-AM codes in the readmission. A change in documentation and coding procedures during a return admission could utilise diagnosis codes to identify that they were previously misdiagnosed or mistreated previously, which would simplify automated methods of identifying that a misdiagnosis or mistreatment had led to the readmission.

5.2 Limitations and future work

Within the scope of this research, there were a great deal of limitations. The most obvious limitation was the small sample size available in Northern New South Wales Local Health District's audit. There were only 109 records determined to be preventable out of the 460 unplanned hospital readmissions included in the audit, of which 77 were maintained once clinician opinions and duplicates were accounted for. The transition to community care and community care factors had two and three patients identified respectively, greater numbers are needed to develop and validate an algorithm capable of identifying these factors. Furthermore, many records did not have additional notes indicating preventable factors of readmission. In addition to the small sample size and the unlabelled records in the audits, the final ICD-10-AM codes in the linked dataset were also limited in how descriptive they were of an admission due to previous coding and documentation standards in the NNSWLHD region. Discussions with the director of the Northern NSW LHD, confirmed that since the audit was conducted, the LHD has implemented strategies for improved diagnosis coding, including referring complex coding cases to more experienced coding staff and extra training for healthcare professionals when providing the documentation that coding staff use to code the admin data. Providing auditors with improved ways to review the notes on both the readmission and the index admission would also improve the completeness and reliably of the audit. During workgroup meetings involving Local Health District directors, offers were made to perform a new higher-quality audit on a larger scale to provide a more comprehensive analysis of the preventable factors. Re-running pyLape over a larger, more informative dataset would provide higher confidence and greater insights into its performance.

The second major limitation was the inaccuracy of the algorithm to determine if a readmission was associated with new condition, different from that of the index admission. This particular component of SQLape was proprietary and not able to be recreated from the published articles and as such was highly inaccurate, causing extreme Type I errors before this step was excluded from the analysis. An Australian specific grouping algorithm that provides more accurate links between index and return admission would greatly improve this step. As there were a large number of unknown factors that led to readmission in the dataset used here, being able to isolate a significant and reliable fraction of them would greatly improve the usefulness of pyLape.

5.2.1 Real world implementation

This is a first step into utilising automated measures of potentially preventable readmissions as an reliable, easy-to-use indicator of quality of care. More testing to validate pyLape in NSW on larger datasets and using higher-quality audits is required. Being able to determine potentially preventable readmissions due to hospital and transition to community factors in an automated fashion will allow hospitals to make better preventative decisions based on evidence.

With the very high specificity found by pyLape, one potential use for the current standard is for pre-screening cohorts for future research. One of the major drivers of automating PPHR evaluation is the high cost of manual chart review. A tool like the one proposed in this thesis, could be used to support a chart review process by selection of a smaller subset of patients for review. This use case is helped by the findings in Section 4.5.2 that False Negatives when examining hospital factors were all a form of mistreatment or misdiagnosis in the index admission. These mistreatment and misdiagnosis cases have different causes which may be possible to identify separately. It is hoped that the ability to identify a missed or inaccurate diagnosis/treatment will be developed for future versions of pyLape to improve this section of the algorithm.

The choice to utilise Python as the language of implementation was made with a view towards future use. Python as a language has large support in the research and engineering community with many cutting edge frameworks developed for it. Integrating pyLape into NSW Health's systems from a technical perspective would be a simple task in comparison with other tools. It also interfaces with SAS/SAP systems via a simple call function.

With the ease of integrating this research software into future projects and healthcare systems, the possibilities for extending this research to improve patient care related to potentially preventable readmission are numerous. However further research is required to validate it fully at a large scale.

5.3 Final Words

In the process of researching and working with the people in New South Wales' healthcare system, it was made incredibly clear how important being able to accurately identify potentially preventable readmissions is. Every clinician I spoke to in the course of this project wants patients leaving their care healthy and not coming back to hospital if they can prevent it. I found that, within NSW Health, patient outcomes are the primary concern, and that the cost of improving the population's health, while important, is secondary to improving the population's wellbeing. In this increasingly data-driven decision-making world, clearly defined performance indicators can provide meaningful information to policy makers to ensure sustained improvement of patient outcomes. Algorithms that can identify potentially preventable readmission quickly and cheaply, while being more consistent and accurate than human reviewers, will over time come to be used as the gold standard.

Appendix A

UHR Audit Tool

Health
Northern NSW
Local Health District

Unplanned Hospital Readmissions Audit Tool

Instructions:
Please refer to the Unplanned Hospital Readmissions Audit Tool Guide for definitions and guidance when auditing.

Site ☐ Grafton ☐ Maclean ☐ Ballina ☐ Bonalbo ☐ Casino ☐ Coraki ☐ Kyogle
☐ Lismore ☐ Nimbin ☐ Urbenville ☐ Byron Bay ☐ Mullumbimby ☐ Murwillumbah ☐ The Tweed

MRN ☐☐☐☐☐☐ **DOB** ☐☐ / ☐☐ / ☐☐ **Previous discharge date** ☐☐ / ☐☐ / ☐☐ **Readmission date** ☐☐ / ☐☐ / ☐☐

1. Principal diagnosis - previous admission

2. Principal diagnosis - readmission

3. What was the readmission potentially related to the previous admission? ☐ Yes ☐ No

4. What was the readmission category as documented in EMR? ☐ Planned ☐ Emergency ☐ Inter-hospital transfer

5. Is the readmission category as documented in EMR correct? ☐ Yes ☐ No

IF READMISSION IS NOT POTENTIALLY RELATED NO FURTHER QUESTIONS APPLY

6. Patient's functional status (regarding ADL): ☐ Independent ☐ Somewhat dependent ☐ Fully dependent

7. Patient's disposition after previous admission: ☐ Home ☐ Aged Care ☐ Sub acute/transitional care ☐ Other

8. End-stage chronic disease:

a. Is the patient likely to die in the next 12 months?
☐ Strongly agree ☐ Agree ☐ Unsure ☐ Disagree ☐ Strongly disagree

b. Is the patient likely to go into residential care in the next 12 months?
☐ Strongly agree ☐ Agree ☐ Unsure ☐ Disagree ☐ Strongly disagree ☐ N/A (Patient already in aged care)

9. At the time of the previous admission, what was the Ontario HARP score for this patient? (see page 2) ☐☐

10. Please indicate whether any of the following preventable factors were relevant to this readmission:

a. Factors related to hospital care during the previous admission:
☐ *Missed or inaccurate diagnosis*
☐ *Missed or inappropriate treatment*
☐ *Complication of a procedure*
☐ *Healthcare associated infection*
☐ *Venous thromboembolism*

b. Factors related to transition from hospital to community-based care:
☐ *Transition planning*
☐ *Discharge summary*
☐ *Patient education*
☐ *Clinical handover to community-based care*

c. Factors related to community-based care:
☐ *Primary care planning*
☐ *Access to GP or Medical Specialist*
☐ *Medication management*
☐ *Access to community health services*
☐ *Access to personal care (e.g. Home Care, ComPacks)*
☐ *Poor coordination of community-based care*
☐ *Access to suitable models of chronic care (e.g. cardiac/respiratory)*
☐ *Inadequate transport*

d. Patient factors:
☐ *Patient decision (against recommended care)*
☐ *Patient compliance/self-management*
☐ *Patient awareness of community-based services*
☐ *Currently being managed for a mental health condition*
☐ *Impaired cognitive state (e.g. dementia)*
☐ *Can't afford medicines*
☐ *Can't afford personal care*
☐ *Can't afford transport*
☐ *Social isolation (e.g. living alone, not socialising, isolated from family)*
☐ *Failure to recognise worsening symptoms (>2 days)*

e. Other factor/s: *(please specify)*

11. Was the readmission preventable? ☐ Strongly agree ☐ Agree ☐ Unsure ☐ Disagree ☐ Strongly disagree

V2.0 4352610900

Unplanned Hospital Readmissions Audit Tool

Table 1: The simple algorithm for the previous admission

Variable name	Parameters	Assigned Score	Maximum score for variable	Score for this patient
Patient age group	0 - 64 years old	0	3	
	65-84 years old	2		
	85+ years old	3		
Discharge disposition	Transfer to home / other	0	6	
	Transfer to home with support	4		
	Transfer to acute care	6		
Acute care admission six months prior	0	0	12	
	1	3		
	2	6		
	3 +	12		
Emergency department visits six months prior	0	0	10	
	1	4		
	2	6		
	3	7		
	4 +	10		
Diagnosis Group (more than one may be applicable)	Chronic Obstructive Pulmonary Disease	3	10	
	Heart failure w/out coronary angiogram	4		
	Inflammatory bowel disease	5		
	Gastrointestinal obstruction	2		
	Cirrhosis/alcoholic hepatitis	10		
	Diabetes	1		

EXPLANATORY NOTES:

Unplanned Hospital Readmissions (UHR) is a performance measure in the LHD Service Agreement.

- Indicator definition: <u>Unplanned</u> readmission of a patient within 28 days following discharge to the same facility for any purpose other than mental health, chemotherapy or dialysis.
- Mental health, chemotherapy or dialysis are excluded from both the numerator (readmissions) and the denominator (admissions). More specifically, the exclusions are:
  - Readmissions that contain a cancer code (code between "C00" and "D48.99") in any diagnosis field.
  - Readmission for chemotherapy or dialysis (DRGs R63Z or L61Z).
  - Readmission for mental health (where patient has been admitted to psychiatric unit > 0 days).
  - Change of care type, transfers from other hospital (i.e. source of referral 4 or 5).
  - Facilities in peer groups below D2.
- Unplanned is defined as emergency_status = 1.

Notes:

- There is no "unexpected" in the UHR definition.
- Don't be dismayed by readmissions not related to the previous admission. In practice, we find approximately one half of all UHR are potentially related to the previous admission - we are focusing upon this half. A State-level working group is currently reviewing the indicator definition.
- The hospitals that matter most for the LHD Service Agreement are the hospitals which have activity-based funding for acute services (Tweed Heads, Murwillumbah, Lismore, Ballina and Grafton).
- Improving data quality:
  - Ensure planned admissions are not coded as unplanned (emergency_status = 1).
  - Ensure patients transferred from acute inpatient admission to hospital-in-the-home (HITH) are being correctly coded.
  - Ensure readmissions which occur on the day of discharge are being correctly coded.

Unplanned Hospital Readmissions Audit Tool

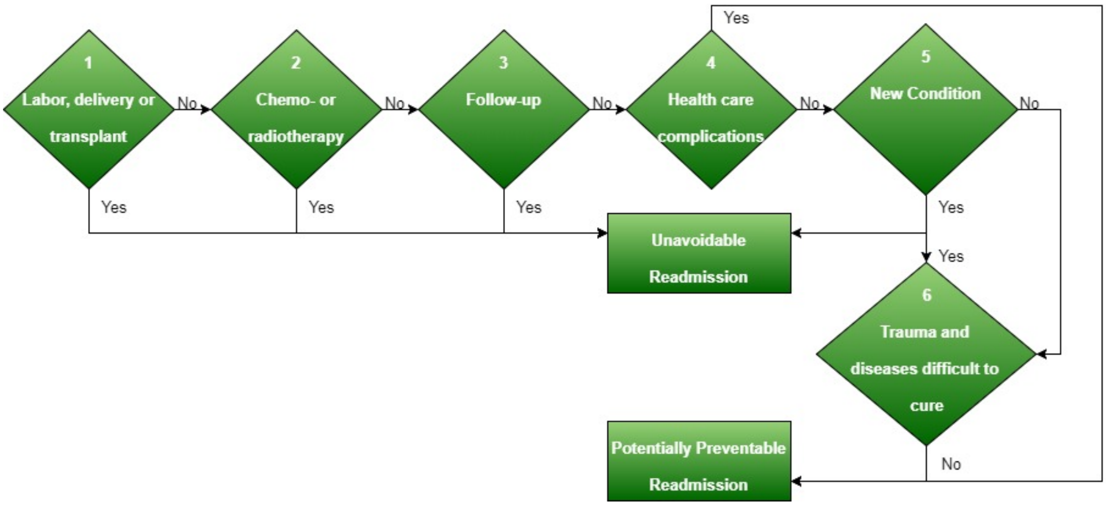
The purpose of this UHR Audit Tool is to identify practical factors which can be used to prevent UHR at your hospital. This will enable better targeted strategies to be planned and implemented to prevent UHR. Although it can be used for retrospective audit, the UHR Audit Tool is best used at the time of readmission.

Hospital Admission Risk Prediction (HARP)

This HARP predictive tool is used for early identification of people at-risk of hospitalisation within the next 30 days. This particular tool was developed for use in Ontario, Canada. With the ultimate aim of people at a higher-risk of UHR within 28 days being allocated higher priority for well-targeted strategies to prevent UHR, we are trialling the utility of using this predictive tool. We anticipate this version of the tool will be replaced in the future by a similar predictive tool for people at-risk of UHR within 28 days, which is based upon NSW Health UHR data.

Appendix B

pyLape Definition



Note that for all codes in the following section, periods and hyphens have been removed (i.e. A12.3 will be written as A123).

Also, each code includes all child codes. So if a patient has 5051 it will match to the 505 in the tables below.

* Diseases that are considered difficult to cure in Step 6 are: Idiopathic thrombocytopenic purpura, myelodysplastic syndrome, multiple sclerosis, cirrhosis of liver, urinary calculus, acute bronchiolitis of nurseling, non-surgical intestinal adhesion

Table B.1: List of Potentially Avoidable Causes of Readmission Steps 1-4

Step	Conditions	ICD codes
1	Obstetrical conditions as readmission diagnosis	P
1	Organ transplants as readmission procedure	0794, 335, 336, 3751, 4194, 4697, 505, 528, 556
1	Leucopherese, bone marrow grafts in readmission	410, 9972-9974
2	Agranulocytosis after chemotherapy as readmission diagnosis	D70
2	Chemo- or radiotherapy treatment as readmission diagnosis	Z510-Z512
2	Chemo- or radiotherapy treatment as readmission procedure	922, 9925
3	Treatment follow-up as readmission diagnosis	Z08, Z09, Z42, Z44-Z47
3	Rehabilitation as readmission main diagnosis	Z50
3	Rehabilitation as readmission main procedure	9339
3	Procedure not carried out in index as readmission diagnosis	Z53
4	Possible surgical complications as readmission main diagnosis	J850-J853, J860, J869, M000-M002, M008-M009, M462, M463, M862-M864, M866, M868, M869, T81, T838, T848, T889, T889, Y6
4	Other healthcare complications as readmission diagnosis	E86, I460, I461, I469, K316, K382, K603, K604, K632, K661, K823, K832, K833, K922, N321, N322, N82, O678, O679, O95, O960, O961, O969, O970, O971, O979, R048, R049, R570 - R572, R578, R579, R58, R960, R961, R98, R99, T793
4	Preventable diseases as main readmission diagnosis	I260, I269, I801 - I809, I820 - I829, L89

TABLE B.2: List of Potentially Avoidable Causes of Readmission Steps 5-6

Step	Conditions	ICD codes
5	New medical condition, by damaged system if system match in readmission main procedure or diagnosis with any damaged in index admission	Refer to Table B.3
6	Trauma as main readmission diagnosis	K131, L550-L552, L559, M125, M242-M244, M483, M626, M660-M665, M843, M992, S00-S99, T00-T35, T691, Z57, Z584, Z585
6	Diseases difficult to cure as main readmission diagnosis*	D693, G35, K700, K703, K717, K746, N20, N21, N220, N228, N23, R18
6	Packed cell transfusion (9904) as readmission procedure and as any readmission diagnosis	D46, D570
6	Platelet transfusion (9905) as readmission procedure and as any readmission diagnosis	D694-D696
6	Intestinal obstructions/adhesions relapses where both index and readmission main diagnosis	K565, K660
6	Therapeutic photopheresis (9988) as readmission procedure and as any readmission diagnosis	T860, T862, T863, T868

TABLE B.3: Step 6. New medical conditions

System	Diagnosis or Procedures
Circulatory	D5-D8, I, R00-R03, R7, 28, 39-45
Cutaneous	L, R20-R23, 68-70
Digestive	K, R1, R85, 00, 52-57
Endocrine	E, 249, 25
ENT	H6-H9, 38
Female	N6-N8, O, R87, 61-67, 71
Locomotion	M, R25-R28
Mental	F, R4, 29-31
Neural	G, R83, 045-049, 32-35
Newborn	P, 72, 73, 76, 77
Ocular	H0-H5, 36-37
Respiratory	J, R04-R07, R84, 46-51
Urinary	N0-N3, R3, R80-R82, 59

Appendix C

Ethical Approval Letters

The following pages contain the ethical approval for the project and the amendment approval letters.

Appendix C of this thesis has been removed as it may contain sensitive/confidential content

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