The effect of comorbidity on injury outcomes: developing and validating ICD-10 based injury comorbidity indices

Dasamal Tharanga Fernando

PG Dip Env Water Res Mgmt; B.Sc. (Hons)

A thesis submitted for the degree of Doctor of Philosophy at

Monash University in 2020

Monash University Accident Research Centre

Copyright notice

Abstract

Aim

Injuries often result in adverse outcomes, and pre-existing comorbidities increase the likelihood of such outcomes. Appropriately quantifying the associations between comorbidity and outcomes is important in clinical settings, research and administration.

Past research recommends the use of outcome- and study-specific comorbidity indices. To date, however, there are no outcome-specific indices for *all* injury patients. This thesis aims to derive and validate indices that capture the effect of comorbidity on injury outcomes. Comparisons are made with the frequently used Charlson Comorbidity Index (CCI) and the Elixhauser Comorbidity Measure (ECM).

Methods

An analysis of retrospective data was carried out, using linked hospital-morbidity and mortality data from the State of Victoria, Australia. Two injury patient cohorts were selected for index derivation from the Victorian Admitted Episodes Dataset (VAED). The first were patients with an index hospital admission between 01 July 2012 and 30 June 2014 (161,334 patients); followed up within the VAED for burden, complications, readmissions and in-hospital death. The second were patients with an index admission between 01 July 2006 and 30 June 2015 (614,762 patients) followed up for mortality (e.g., 30-days, 1-year) in the Victorian Death Index.

Multivariable regression models were used to establish associations between comorbidity and injury outcomes. The newly derived comorbidity indices, the CCI and ECM were validated using subgroups of the Victorian data, and full hospital-admitted injury cohorts from the states of New South Wales (NSW) and Western Australia (WA).

Results

Age and injury characteristics were found to be the greatest contributors to the risk of most adverse outcomes for injury patients. Associations between comorbidities and outcomes varied by outcome. The Australian Injury Comorbidity Indices (AICIs) derived in this thesis performed equally well or outperformed the CCI and ECM in terms of predictive abilities, and outperformed them in terms of relevance and parsimony. Variations were observed in subgroup validations of the AICIs. The performance of some AICIs were similar or better for children and non-severe injury compared to the full cohort, while most AICIs' performance was poorer for older adults and hip fractures. External validations indicated that the AICIs are more robust for use in WA than NSW. Overall, the AICIs validated better than the CCI, and equally well as the ECM in subgroups and on interstate data.

Conclusions

This thesis addressed past recommendations to derive outcome- and population-specific indices; providing internally and externally validated injury comorbidity indices. The varying performances in population subgroups indicate a lack of other relevant baseline factors in this thesis rather than a need for subgroup-specific index derivations. The varying performances in two other States point more towards differences in data-capture than a lack of robustness of indices. A major contribution to the knowledge base surrounding comorbidity indices from the study was the validation of the frequently used CCI and ECM in large injury populations and the conclusions regarding their suitability for use with injury patients. Given the findings from this study, comorbidity indices could be best used for quantifying the risk of outcomes from injury-related processes adjusting for comorbidity presence.

Publications during enrolment

1. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **Effect of comorbidity on injury outcomes: a review of existing indices**. *Ann Epidemiol* 2019, **36**:5-14.

2. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study**. *BMC Public Health* 2019, **19**(1):798.

3. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **The Australian Injury Comorbidity Index to Predict Mortality**. *Ann Emerg Med* 2020, **75**(3):339-353

Ethics approval

The study was approved by the Monash University Human Research Ethics Committee (Project no: 1256), the New South Wales Population and Health Services Research Ethics Committee (REF: 2017/HRE0601) and the Department of Health WA Human Research Ethics Committee (RGS0000000613).

Thesis including published works declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes three original papers published in peer reviewed journals and two submitted publications which are under review at the moment. The core theme of the thesis is injury outcomes. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the Monash University Accident Research Centre under the supervision of Associate Professor Janneke Berecki-Gisolf.

The inclusion of co-authors reflects the fact that the work came from active collaboration between researchers and acknowledges input into team-based research

In the case of chapters 1,3,4,5 and 6 my contribution to the work involved the following:

Thesis Chapter	**Publication Title**	**Status** *(published, in press, accepted or returned for revision, submitted)*	**Nature and % of student contribution**	**Co-author name(s) Nature and % of Co-author's contribution***	**Co-author(s), Monash student Y/N***
1	Effect of comorbidity on injury outcomes: a review of existing indices	Published	Conceptualisation, data collection and writing manuscript: 70%	J. Berecki-Gisolf: input into manuscript 15% S. Newstead: input into manuscript 5% Z. Ansari: input into manuscript 10%	No
3	Complications, burden and in-hospital	Published	Conceptualisation, data collection, analysis and	J. Berecki-Gisolf: input into concepts and manuscript 15%	No

	death among hospital treated injury patients in Victoria, Australia: a data linkage study		writing manuscript: 70%	S. Newstead: input into manuscript 10% Z. Ansari: input into manuscript 5%	
4	The Australian Injury Comorbidity Index to Predict Mortality	Published	Conceptualisation, data collection, analysis and writing manuscript: 70%	J. Berecki-Gisolf: input into manuscript 15% S. Newstead: input into manuscript 10% Z. Ansari: input into manuscript 5%	No
5	Australian Injury Comorbidity Indices (AICIs) to predict burden and readmission among hospital-admitted injury patients	Under review	Conceptualisation, data collection, analysis and writing manuscript: 70%	J. Berecki-Gisolf: input into manuscript 10% S. Newstead: input into data analysis and manuscript 15% Z. Ansari: input into manuscript 5%	No
6	The Australian Injury Comorbidity Indices (AICIs) to predict complications and critical care use among hospital-admitted injury patients	With editors	Conceptualisation, data collection, analysis and writing manuscript: 70%	J. Berecki-Gisolf: input into data analysis and manuscript 20% S. Newstead: input into manuscript 5% Z. Ansari: input into manuscript 5%	No

I have renumbered sections of submitted or published papers in order to generate a consistent presentation within the thesis. However, references have not been renumbered and are presented as they appear in the published works or submitted manuscripts. Supplemental material of all papers/manuscript are attached right after the paper/manuscript for readability.

Student name: Dasamal Tharanga Fernando

Student signature: **Date: 17/04/2020**

I hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author I have consulted with the responsible author to agree on the respective contributions of the authors.

Main Supervisor name: Janneke Berecki-Gisolf

Main Supervisor signature: **Date**: **17/04/2020**

Revisions added based on Examiners' comments.

Changes to manuscripts' status as of the date of these revisions; the 5th manuscript is under review at BMC Health Services Research and the 6th manuscript has been published in PLOS ONE.

Student signature: **Date: 10/10/2020**

Main Supervisor signature: **Date: 10/10/2020**

Acknowledgements

"This research was supported by an Australian Government Research Training Program (RTP) Scholarship."

To my supervisors;

Janneke – Words are not enough to express my gratitude. You have been a mentor, supervisor, mother-figure, gate-keeper, enforcer, and psychologist to me. I am a changed person because of your positive influence. I hope there will be many more students who will get the opportunity to be mentored by you; I consider it a privilege. Again, a 'thank you' is not enough.

Stuart – You have consistently been available, despite managing a busy schedule. Having you as my statistical advisor, I was confident I was being guided by the best. Thank you for everything, including your sense of humour, which on a dull-day brought on a few laughs.

Zahid – Your guidance was focussed on ensuring future success for myself and my work. Your encouragement and guidance meant a lot. Thank you also for helping with data acquisitions and the numerous other requests I kept sending your way.

I would like to thank the Centre for Victorian Data Linkage, the Centre for Health Record Linkage in New South Wales and the Western Australian Data Linkage Branch for providing linkage services and the data. Special thanks to the relevant data custodians, namely for the Victorian Admitted Episodes Dataset, Admitted Patient Data Collection in NSW, the Hospital Morbidity Data Collection in WA, the Registrar of Births, Deaths and Marriages in Victoria and NSW and the Australian Bureau of Statistics (cause of death data for WA).

Special thanks go out to Dr. Sophie Pointer at Flinders University in South Australia for very kindly providing the peer review for this project, at short notice. I am also very grateful to Professor James Harrison for sharing the survival risk ratios for use in my study.

This PhD was initiated and supported by the Victorian Injury Surveillance Unit, supported by the Department of Health and Human Services. I am privileged to have been offered this opportunity and the extensive support provided in terms of finances and supervision.

Angela Clapperton – thank you for being my sounding board, answering my myriad of questions and helping me with my presentations. Thanks also to Assoc. Prof. Jennie Oxley, Assoc. Prof. Sjaan Koppel, Aleksandra Natora and Samantha Bailey for your advice and support during this journey.

Amma and Thaththa (my parents) - every time I took a step back in my life, you both held my hands and took two steps forward with me. My determination to complete this is your influence on me to 'never give up' until I have done all I can. Mum, thank you for covering me in prayer. Dad, I know you would have been the proudest.

My darling husband, Dilshan, my tower of strength, if I can split the title 'PhD', I'd give you the best half. If you did not 'do' and 'be' all that you were during this long journey, I would not be writing this.

My beautiful daughter Teleetha, on the toughest days, I knew I was still a winner, for I had YOU. You helped me maintain my sanity, reminded me to breathe and did the silliest things to make me smile.

My church family, especially Margot, for upholding me in prayer.

Most importantly, I give all glory to my God, for in Him lies all my strength!

Table of contents

List of tables

Chapter 4 – paper

Chapter 5 – paper

Chapter 6 – paper

List of figures

Chapter 6 – paper

Abbreviations

APDC	Admitted Patient Data Collection
AIC	Akaike Information Criterion
AUC	area under the curve
AUROC	area under the receiver operating characteristic curve
AUD	Australian dollar
AICI	Australian Injury Comorbidity Index
AR-DRG	Australian Refined Diagnosis Related Groups
CCU	Cardiac Care Unit
COD-URF	Cause of Death – Unit Record File
CHeReL	Centre for Health Record Linkage
CVDL	Centre for Victorian Data Linkage
CCI	Charlson Comorbidity Index
CDS	Chronic Disease Score
CHADx	Classification of Hospital-Acquired Diagnoses
CI	confidence interval
CCS	critical care services
DLB	Data Linkage Branch
DM	diabetes mellitus
DALY	disability adjusted life years
ECM	Elixhauser Comorbidity Measure
FN	false negative
GBD	Global Burden of Disease
HMDC	Hospital Morbidity Data Collection
HIV/AIDS	human immunodeficiency virus/acquired immunodeficiency syndrome

IRR	incident rate ratio
ICU	Intensive Care Unit
ICISS	International Classification of Disease-Based Injury Severity Score
ICD	International Statistical Classification of Diseases and Related Health Problems
IQR	inter-quartile range
LOS	length of stay
MV	mechanical ventilator
MORT	Mortality Risk for Trauma
MACSS	Multipurpose Australian Comorbidity Scoring System
NSW	New South Wales
NCD	non-communicable disease
OR	odds ratio
RBDM	Registrar of Births, Deaths and Marriages
SEIFA	Socio-Economic Indexes For Areas
SQLape	Striving for Quality Level and analysing of patient expenditures
SRR	survival risk ratio
TRISS	Trauma and Injury Severity Score
TBI	traumatic brain injury
VAED	Victorian Admitted Episodes Dataset
VDI	Victorian Death Index
WA	Western Australia

1 Introduction

This chapter includes a paper which was published in *Annals of Epidemiology* titled

"Effect of comorbidity on injury outcomes: a review of existing indices"

(attached at the end of the chapter)

Fernando DT, Berecki-Gisolf J, Newstead S & Ansari Z (2019a) [1]

1.1 Background

Injuries often result in adverse outcomes, and pre-existing comorbidities increase the likelihood of such outcomes. Injury-related outcomes by themselves could be life-threatening, or lead to functional impairment or permanent disability resulting in poor quality of life. When injuries require patient admission to *hospital*, there are specific adverse outcomes that could arise, during hospital stay and post-discharge, leaving a burden on the patients, their families, the hospitals and long-term-care support services.

The presence of pre-existing comorbidities (e.g., chronic diseases) increases the likelihood or gravity of some outcomes such as subsequent death, increased length of stay in hospital (LOS), increased costs, readmissions, development of complications, use of critical care services and the need for long-term nursing care. This research aims to conduct an in-depth investigation on how injury and comorbidity interact with each other, and impact patients and the healthcare system in terms of some of these outcomes, for all hospital-admitted injury patients in the state of Victoria, Australia. The process will involve the development of indices that capture the effect

of comorbidity on injury outcomes in Victoria, and, validation of the indices in the Australian states of New South Wales (NSW) and Western Australia (WA).

The aims of this chapter are to: (1) provide an overview of the *global* burden of disease and injury, and injury burden in *Australia*, (2) introduce some of the terminology in this domain, (3) describe the role of comorbidity on outcomes of injury patients, (4) present the methods currently available for quantifying comorbidity, methods used to derive existing comorbidity indices, their capabilities, drawbacks and evolution to-date, (5) discuss the various measures of injury outcomes and (6) reveal some of the knowledge gaps in quantifying comorbidities for injury outcomes research. The chapter also states the aims of the entire thesis and the research questions to be addressed, and ends with a brief outline of the thesis structure.

The main content of the chapter is based on a literature review. A narrative review of literature going as far back as the 1940s was carried out using specific themes in a chronological order. The relevant information was recorded using a study-specific data collection form. A systematic literature review was however not conducted as the purpose of the literature review in this instance was to position the study in the context of what has gone before and what is currently taking place, which was adequately covered with a narrative review. Overall, more than 300 articles were reviewed, sourced from Google, PubMed and Google Scholar search engines.

1.2 Global disease and injury burden

Injury and disease are recognised globally as major sources of disease burden resulting in mortality, loss of functional health and disability to individuals, and costs to healthcare and social service systems. This constantly warrants attention from authorities to develop strategies to assist those affected and set up prevention

measures to reduce the incidence and outcome impact resulting from injury and disease.

The Global Burden of Disease (GBD) 2004 [2] Update report showed that non-communicable diseases (NCDs) account for nearly half of the disease burden among low- and middle-income countries and this proportion was even greater in the high-income countries. In high-income countries, this mainly correlated to the population structure and the increased risk of NCDs among the older age groups [2].

In 2004, injuries accounted for one-sixth of the global burden of disease among adults, and road-traffic accidents were the third leading cause of burden among those aged 15-44 years. Violence and self-inflicted injuries were also among the 10 leading causes. Interestingly, the rate of disability adjusted life years (DALYs) globally due to injury has been dropping since 1990. The rate of injury incidence had also dropped during the same period. However, the rate of the decrease in DALYs were higher than the rate of the decrease in incidence [3]. The slower decline in the rate of incidence of injury to DALY rates implies the presence of multiple mechanisms underpinning these patterns. The decrease in injury incidence could be attributed to measures taken to reduce injury occurrence such as road safety, gun control or the use of safer tools in industry. The larger decrease in DALY rates could be attributed to measures taken to increase the survivability of or full recovery from injuries; through injury mitigation countermeasures such as seat belt and helmet laws or through improved access to quality trauma care [3].

1.3 Disease and injury burden and trends in Australia

According to the GBD project for 2012 [4], out of the 147,000 deaths in Australia, 90% were related to NCDs and 6% due to injury, which is close to the current

global statistic (8.6%). In 2018, 90% of deaths in Australia had a chronic disease as an underlying cause while 6.8% were due to injury [5]. The mortality rates (injury plus disease) of those living in remote and very remote Australia were 1.4 times higher than those living in major cities.

The age-standardised rate of injury hospital admissions in Australia had risen at an average rate of 1.1% per year during the period 2007/08 to 2016/17 [6]. In 2016/17, there were 530,000 injury admissions, and 55% of them were male, 31% were over the age of 65 years (among females it was even higher at 42%) and the leading cause was falls (41%). Rates of injury admissions rose steeply as the distance from major cities increased, with the rates more than double in very remote areas compared to cities (4,337/100,000 population vs, 1,964/100,000 population).

1.4 Definitions

1.4.1 Injury

Injury could be defined using theoretical and operational concepts which include external causes and pathology. This project specifies injuries using external cause definitions. These are injuries commonly defined as ‘caused by acute exposure to physical agents such as mechanical energy, heat, electricity, chemicals, and ionizing radiation, interacting with the body in amounts or at rates that exceed the threshold of human tolerance’ according to Baker, O'Neill and Karpf (1992) [7].

1.4.2 Chronic Disease

A chronic disease is defined as a disease lasting three months or longer [8]. Chronic diseases generally cannot be prevented by vaccines or cured by medication, nor do they just disappear. Chronic diseases can take the form of communicable diseases (passed on from person to person, e.g., HIV/AIDS (human immunodeficiency

virus/acquired immunodeficiency syndrome) and NCDs (not transmitted from person to person, e.g., diabetes, heart disease, cancer).

1.4.3 Outcome

An outcome is defined as the way something turns out; a consequence. According to New South Wales Health, a health outcome is defined as a 'change in the health of an individual, group of people or population, which is attributable to an intervention or series of interventions' [9]. The intervention may be controlled or uncontrolled.

1.4.4 Comorbidity

'Comorbidity' was defined by Feinstein in 1970 [10] as "any distinct clinical entity that has co-existed or that may occur during the clinical course of a patient who has the index disease under study". This describes comorbidity as the presence of one or more additional diseases (or conditions) co-occurring with a primary (index) disease or condition; or the effect of such additional conditions. The term co-morbidity also includes 'non-disease' clinical entities such as pregnancy, deliberate dieting in an effort to lose weight and certain symptomatic reactions, such as nausea, that may occur with various therapeutic manoeuvres [11]. For the purposes of this study, *pre-existing chronic diseases* are considered as "comorbidities" while conditions or diseases that develop during the admission and are not present *at* admission are considered as "complications".

1.4.5 Index

An index is generally a sign or measure of something which could include a combination of features. In this study the term index will be used to define a measure of the extent of comorbidity. This measure could take various forms including a sum

of binary responses (for each comorbid condition) or a score created by summing up individual weights (based on its effect on an outcome) obtained for each comorbidity.

1.5 Comorbidity and injury outcomes

The co-occurrence of injury and comorbidity are likely to increase chances of adverse outcomes. In certain population groups, more commonly among older adults, injury and chronic diseases are likely to co-occur; the result worse than the sum of its parts. Furthermore, former studies have demonstrated that injured people are also more likely to exhibit pre-existing morbid conditions over the non-injured [12, 13]. Outcomes and complications potentially differ for a person who incurs an injury while having one or more co-morbid conditions, as opposed to a person with no co-morbid conditions (e.g., wound recovery for a diabetic patient could take longer than for a non-diabetic). This substantiates the need for establishing the estimated prognostic effects for those experiencing the combination of injury and disease. The following discussion of comorbidities and health outcomes, though not particular to injuries, holds true for injury patients as well.

1.5.1 The importance of the association between comorbidity and outcomes

Valderas, Starfield, Sibbald, Salisbury and Roland (2009) [14] discussed the importance of the correct constructs in defining comorbidity. They highlighted that the nature of the health condition, the relative importance of the co-occurring conditions, the chronology of presentation of the conditions and expanded conceptualizations were distinctive in defining comorbidity. Differentiating the distinct nature of the comorbid conditions (e.g., presence of anxiety and depression may not be considered as two different comorbidities), identifying index and non-index conditions, identifying complications, time and sequence of conditions and patient characteristics are

considered important. The constructs should depend on the setting and application, such as clinical care, epidemiology and public health or resource allocation. In health service research, especially in resource allocation, the interactions or the sum of effects of co-existing conditions are considered as important determinants [14].

1.5.1.1 Key domains where comorbidity plays a vital role in injury

1.5.1.1.1 Clinical care

In clinical care, the ability for the comorbidity construct to inform patient management matters. For example, comorbidity is crucial in specialist care while multimorbidity and morbidity burden are important to primary care. Further, the presence of comorbidity affects a patient's clinical course. This results in different outcomes for the same index disease for patients with and without comorbidity depending on the number and type of comorbidities present [10]. Among injury patients, injury severity is affected by comorbidity; inter-relationships and effects of multiple diseases could aggravate an otherwise non-severe injury to a critical level.

Two studies found that comorbidity was associated with Intensive Care Unit (ICU) stay and mechanical ventilator (MV) use among injury patients [15, 16]. Another assessed the same among traumatic brain injury (TBI) patients with and without diabetes mellitus (DM), and concluded that associations between comorbidity and the outcomes such as MV days and surgical ICU-LOS were *not* significant. This means that among trauma patients, the effect of comorbidity on outcomes of clinical care varies with the study group and the outcome of interest.

1.5.1.1.2 Epidemiology and research

Feinstein (1970) [10] emphasised the fact that outcomes could be severe or death could come sooner to patients due to the presence of comorbidity than just the

presence of the index disease alone. Their recommendation was that it is imperative to use information on comorbidity in calculating survival rates. Two examples are given below.

In epidemiological research, disease-specific *mortality rates* for a general population are calculated based on a single cause of death from the cause of death records, even though there may have been other diseases that may or may not have contributed to the death. For example, if a patient had coronary artery disease and DM, the mortality rate could be biased towards coronary artery disease if that was listed as the underlying cause of death, though it could have been the combination of the two that resulted in the death [10].

Alternatively, *fatality rate calculation* for a particular condition involves the division of the number of deaths due to the condition by the number of people with the condition. Should some of the deaths be due to a co-morbid condition and not the index condition, the fatality rates of the index condition becomes unnecessarily inflated [10].

Therefore, the separation of index diseases from comorbidity, and identification of the correct cause or combination of contributing risks for an outcome is crucial for drawing reliable conclusions in epidemiological research.

1.5.1.1.3 Health and social service planning and financing

Short- and long-term planning and financing of health care and social services are reliant on information on projected resource needs for immediate and after-care of patients. The confounding effects of comorbidity on trauma patients could increase the resource needs, warranting adequate planning and fund allocations.

It has been shown that comorbidity gives rise to increased LOS in hospital, and complications such as readmission to hospital [17]. Furthermore, the long-term functional outcomes of injured persons are affected by the presence of comorbid conditions [18]. Lustenberger et al. (2013) [19] assessed the discharge disposition of TBI patients with DM and found that most of them were not sent home directly after hospital-care; they were more likely to be discharged to high-care nursing compared to those without DM.

Increased costs related to short-term (hospital) and long-term nursing care is a burden on the health and social welfare systems and to insurers. Charlson, Wells, Kanna, Dunn and Michelen W (2014) [11] found that yearly costs were related more to the total burden of comorbid conditions than a specific condition. Delayed recovery and disability have serious financial and physical implications to the patients and their families, and affects the DALYs of patients.

Further, the current 'Activity Based Funding' model for Australian public hospitals incorporates the Australian Refined Diagnosis Related Groups (AR-DRGs) and case-mix funding. AR-DRGs are worked out based on the principal diagnosis, secondary diagnosis such as complications and comorbidities, medical procedures, age, gender, length of stay and discharge codes. Complications and comorbidities are listed where they have a bearing on the management of the patient and therefore included in calculating the AR-DRGs. Complications and comorbidities are an indication of the type of care needed by a patient, and the amount of funding allocated to a particular episode of care is proportional to the type of care. This relays the importance of the role comorbidity plays in relation to funding allocations in Australia.

1.6 Methods available for quantifying comorbidity

Traditional forms of modelling disease outcomes utilised the diagnosis, demography and anatomy to identify homogeneous groups, and ignored comorbidity or excluded patients with comorbid conditions. In was not until the 1970s, that the inclusion of comorbidity was considered important for more reliable statistical computations [10].

It was Feinstein and Kaplan (1974) [20] who initially classified comorbidity at four levels ranging from 0-3, based on severity, intending to test its effect on prognostic outcomes. They used 'type' of comorbidity (vascular and non-vascular in the case of diabetes patients), 'cogency' of comorbidity and 'severity' of cogent conditions to assess risk of mortality. The final classification went from 0 (non-cogent or no comorbidities) to 3 (full decompensation of vital systems, episodes of life-threatening events for chronic conditions that threatened life), and they concluded that the type and severity of the comorbidity was related to patients' disease outcomes.

Other forms of accounting for comorbidity also eventually evolved: they are (i) the presence of at least one comorbid condition, (ii) count of all comorbid conditions, (iii) presence of each comorbid condition and (iv) weighted comorbidity indices.

1.6.1 Types of comorbidity measures

The literature presents two types of comorbidity indices used to measure the impact of comorbidity on outcomes. *Diagnosis-based indices*, which use diagnosis-codes-based chronic disease indicators; and *medication-based indices*, which use medication-based chronic disease scores to compute a comorbidity score which is then used to assess the outcome of interest.

1.6.1.1 Diagnosis-based chronic disease indices

These indices are derived using diagnosis codes for conditions co-existing with the primary diagnosis, from routinely collected data from administrative databases or medical record review. These could relate to inpatients or outpatients. Some examples of these indices are the Charlson Comorbidity Index (CCI) [21] and the Elixhauser Comorbidity Measure (ECM) [22] along with their various adaptations. They are based on diagnosis codes, and if weights are employed, they are either study-specific weights for various comorbidities or weights borrowed from existing studies.

1.6.1.2 Medication-based chronic disease indices

Medication-based indices use pharmacy data linked to various diseases in order to identify comorbidities. The Chronic Disease Score (CDS) and Rx-Risk are two indices in this group. The first CDS was developed and validated in 1992 by Von Korff, Wagner and Saunders, and included 17 diseases [23]. Over time, various updates and adaptations have taken place and in a publication by Fishman and Shay in 2003 [24], the Rx-Risk index, which is a modified version of the CDS expanding the disease categories with new medications, was developed. The final version of this group was the medication-based disease burden index, which deals with all revisions of the CDS.

The type of data readily accessible to this project was diagnosis-based and therefore this study uses the diagnosis-based method.

The derivation and evolution of existing comorbidity indices and the capabilities and drawbacks of the most frequently used indices (namely the CCI and ECM which are both diagnosis-based) was studied for this project. The findings are available in the published literature review attached at the end of the chapter. The literature review included studies based on injury populations as well as studies not based on injury

populations. Among studies not based on injury, only around 28% had a conclusion of a ‘weak association’ between the comorbidity indices and the outcome (see Table 1 in attached publication). In contrast, among the injury populations, around 50% had a conclusion of a ‘weak association’ between comorbidity indices and the outcomes. By including studies for injury and non-injury populations where comorbidity indices have been validated, it showed that the validation studies on the injury groups were fewer, and that indices derived using general medical populations did not validate in injury populations as well as they did on non-injury populations.

Below is a description of the most frequently used indices, the CCI and ECM.

1.6.1.3 Charlson Comorbidity Index

The CCI was developed on a cohort of patients admitted to New York Hospital in 1984 during a one-month period and then followed up over a course of one year to assess 1-year mortality [21]. All patients’ clinical characteristics, demographics, complications, arrests, deaths, status at discharge, reason for admission, the number and severity of comorbid diseases (19 conditions) were considered for testing predictive possibilities. Completely resolved comorbidities or inactive comorbidities with a history of surgery were excluded. The developed model was validated on a cohort of breast cancer patients. Comorbid diseases were coded as a nominal variable with a binary outcome. Severity of the comorbidities were considered as ordinal variables and age was grouped into a categorical nominal variable. Using proportional hazards modelling techniques and stepwise procedures, unadjusted relative risks (risk of mortality for a given comorbid condition regardless of severity and all other comorbidities and factors) and adjusted relative risks (which considers the presence of all other factors) were assessed. A scoring system was then developed that used the adjusted relative risks. A second score combining age and comorbidity was

derived to estimate the risk for long-term survival. The CCI was updated by Quan et al. in 2011 [25]. The paper by Charlson, Pompei, Ales and MacKenzi (1987) which developed the CCI, has over 29,000 citations according to Google Scholar. Even though developed in 1986, the CCI in one of its *early* forms is still frequently used today (2,343 citations in 2019, as per Web of Science, December 2019).

1.6.1.4 Elixhauser Comorbidity Measure

The ECM [22] is a binary representation of 30 conditions, which includes all but 3 conditions from the CCI. The ECM was derived to predict in-hospital mortality and resource use, and the paper by Elixhauser, Steiner, Harris and Coffey (1998) that developed the ECM has 5,733 citations as of December 2019.

Apart from the CCI and ECM, there is also the Multipurpose Australian Comorbidity Scoring System (MACSS) [26], developed in 2005 by Holman, Preen, Baynham, Finn and Semmens. The MACSS uses 102 conditions; therefore, it is likely to be useful only in large samples with significant prevalence of the diseases. MACSS is not widely used in comparison to the former two (100 citations for the paper that derived the MACSS, as of December 2019 according to Google Scholar).

1.7 Knowledge gaps

Past research recommends the use of outcome- and study-specific comorbidity indices [26-32]. To date, however, there are no indices for mortality-, burden- or complication-related outcomes for *all* injury patients. Therefore, it is uncertain if such new indices would be more effective in capturing the effects of comorbidities for this group than existing measures.

Furthermore, the conditions included in existing indices and the weights allocated to capture their effects may need regular updating, given the continuous

advances made in medical sciences and changes in chronic disease epidemiology. The less frequently used ECM, which is a binary representation of 30 comorbidities, outperformed the more regularly used CCI, which is a weighted index of 19 conditions [32]. However, the ECM has not been sufficiently validated on injury populations. Both indices have shown to perform better for mortality than for resource use [33].

In summary, the existing measures have a number of limitations:

- The validations were confined to specific sub-groups of populations
- Data linkage was less-often used for statistical follow-up of patient outcomes; whereas linkage could improve the trace of outcomes
- The original comorbidity index (CCI) is rather dated (given the advances in medical science and the changes in disease epidemiology over time)
- The large number of comorbidities included in indices like the ECM and MACSS could result in overfitting, and become generally unhelpful in small samples
- The creation of the original indices (e.g., CCI, ECM) were based on index diseases rather than index injury, therefore may not reap reliable results for injury patients
- The CCI's focus was solely to predict mortality outcomes, which may not work as well for other outcomes
- Differing opinions exist on methods for accounting for comorbidity, e.g., weighted summed scores over binary representation of individual conditions, which has not had a very comprehensive evaluation
- Recommendations for study-specific indices have been made, but so far only one such index for injury patients has been derived (Thompson et al., 2010) [31], but this too contains certain limitations [1]

- Recommendations for outcome-specific indices have been made, but the derivations so far in this context were not very specific nor have they been sufficiently validated [26]

1.8 Study aims

The purpose of this thesis is to establish the associations between comorbidity and injury outcomes, and to develop new indices with an optimum representation of these associations, using Victorian administrative datasets for morbidity and mortality. A validation of all existing and new indices will then be carried out on data from other states in Australia to provide comparisons of the indices and test robustness. The outcomes of interest are mortality, readmission to hospital, hospital LOS and costs, complications, use of critical care services such as the ICU, the MV and the Cardiac Care Unit (CCU) and the need for long-term nursing care.

Two main outcomes are expected of this study:

1. From a clinical perspective, to establish which comorbid conditions effect which outcomes. If robust indices could be developed, these could have a role in risk stratification of injury patients with comorbidities, with the used of the information available at hospital-admission, and
2. From a research perspective, to derive up-to-date comorbidity indices for an injury population which will be useful for adjusting for the effect of pre-existing comorbidities in injury epidemiology studies or in actuarial sciences.

1.9 Research questions

Principal research question

How does comorbidity affect outcomes of hospitalised injury patients in Victoria and can the impact of comorbidities effectively be captured in a summary index?

Subsidiary questions

1. What are the outcomes of hospitalised injury in Victoria in terms of complications, readmission, LOS, hospital costs, use of critical care services, discharge destination and survival?
2. Based on the analysis of Victorian data:
   a. How can injury outcomes best be quantified?
   b. How can comorbidity best be quantified?
   c. How do comorbidities affect the outcomes of hospitalised injury patients?
   d. Can the effect of comorbidity be generalised across a range of outcomes?
3. Does an updated comorbidity index perform significantly better than the CCI, updated CCI by Quan et al. and the ECM in predicting injury outcomes?
4. Do the indices' performance (predictive ability) vary among subgroups of the population?
5. Do the indices developed on Victorian data effectively capture the effect of comorbidity on injury outcomes in other Australian states?

1.10 Further findings from the literature review

Apart from gathering details regarding existing comorbidity measures and their evolution, the literature review assisted in assessing the performance of existing

comorbidity measures and identifying outcome measures. These will be used in the design of the thesis.

1.10.1 Measuring outcomes

This section answers the subsidiary question 1: What are the outcomes of hospitalised injury in Victoria in terms of complications, readmission, LOS, hospital costs, use of critical care services, discharge destination and survival?

The literature review assisted in identifying trauma outcomes that have been studied widely in the past. The review included studies that used administrative data as well as registry data and medical chart reviews to identify outcomes. The generally investigated outcomes were mortality, LOS and readmission, and to a lesser extent use of critical care services and discharge disposition. Even less frequently studied were outcomes such as costs, complications and functional capacities (e.g., disability). These outcomes are highly relevant for clinical care and resource allocation. In terms of clinical care, complications are a major concern. Healthcare expenditure on the other hand is vital for health service planning. The outcomes used in this study were mainly based on those mentioned above. The choices were also dependent on the relevance to hospitalised patients, and the possibility of capturing the outcome in hospital administrative data that was linked within itself or to mortality databases. Based on these criteria, three groups of outcomes with a total of 16 different measures were selected initially. They were:

Mortality-related

- In-hospital death
- 30-day mortality
- 1-year mortality

- 5-year mortality
- Time until death (within 10 years)

Burden-related

- LOS – overnight stay
- LOS – time to discharge
- Direct + indirect hospital costs
- All-cause 30-day readmissions
- Non-planned 30-day readmissions
- Potentially-avoidable 30-day readmissions

Discharge destination

In-hospital complications

- CCU (cardiac care unit) stay
- ICU (intensive care unit) stay
- MV (mechanical ventilator) use
- Hospital-acquired complications using the Classification of Hospital-Acquired Diagnoses (CHADx) [34]

Apart from outcomes identified using published studies, CCU stay was studied based on observation of the hospital morbidity dataset in Victoria. Furthermore, CHADx complications were also added to the range of outcomes for study; this is novel and not usually included in comorbidity research. Decisions were also made so that the research would be feasible with outputs that can be tested and utilised in the future, contribute to clinical management of patients and outcomes research.

The above list provides a summary of outcomes to be investigated in this thesis; answering subsidiary question 1.

1.10.2 Performance and abilities of existing comorbidity indices

Binary representation of individual comorbidities, such as used in the ECM, outperformed weighted indices and other comorbidity measures in predicting health outcomes as per the studies included in the review [1]. However, the performance ability of an index was dependent on the data, study population and objectives of the research (whether it was to adjust for comorbidity, predict outcomes, and the outcomes of interest). The ECM, although generally favoured, has not been sufficiently validated in injury populations. Most existing comorbidity indices have proven to be good predictors of mortality outcomes but not of resource use or in-hospital complications. Weighted indices were found to benefit from regular updating of weights using empirical methods to better represent current health care practices. A specific comorbidity index for general injury-populations has not been derived to date, therefore builds the rationale for this thesis.

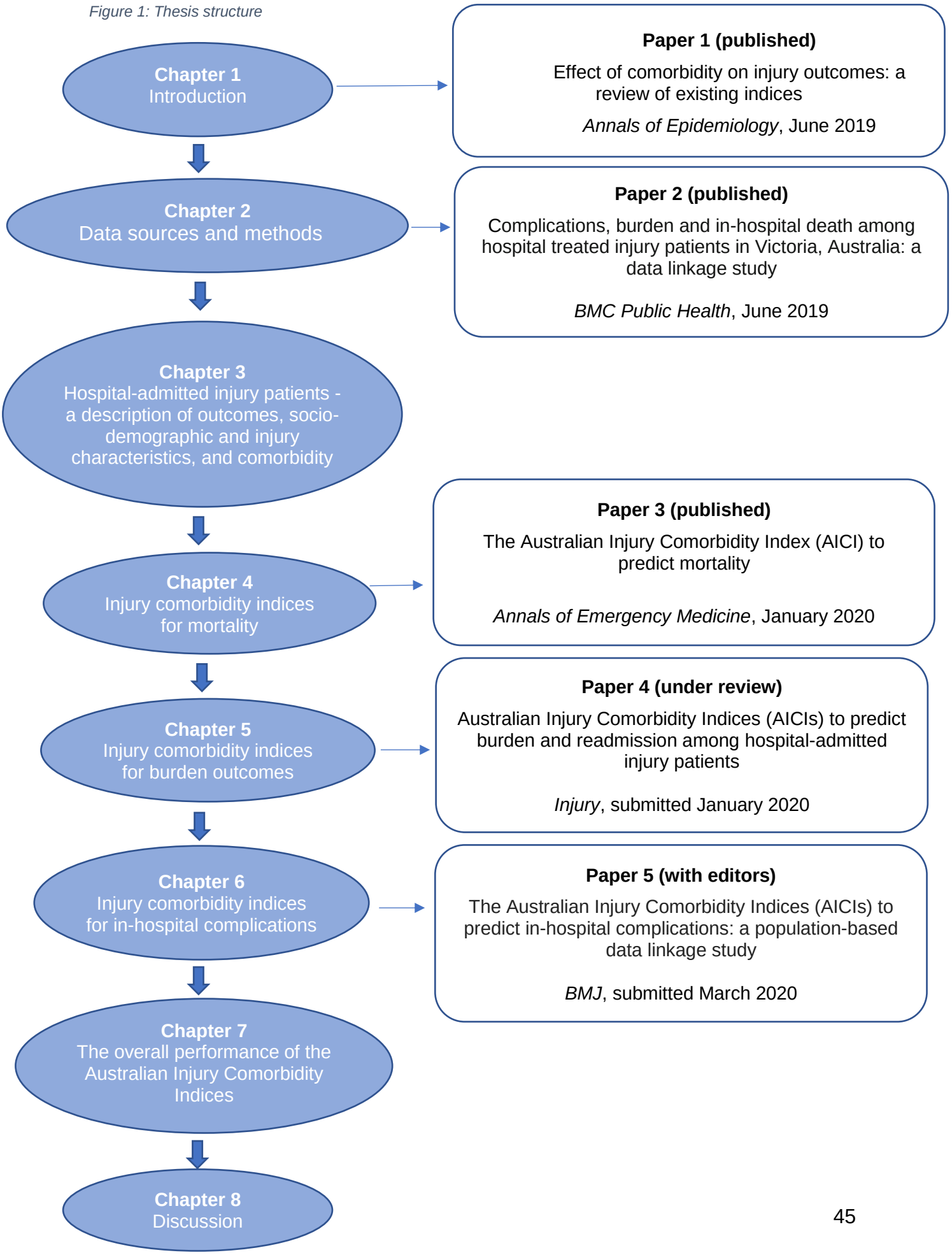
1.11 Potential implications for the thesis

Development of measures to quantify the effect of comorbidity on specific clinical outcomes for general hospital-admitted injury patients is essential for improved quantification of the impacts of comorbidity on health outcomes in future injury epidemiology research. The measures developed should resonate with the present epidemiology of chronic diseases, their clinical relevance, and adjust for the effects of injury-related and socio-demographic factors associated with outcomes. Such an index will eliminate biases introduced by outdated weights and irrelevant comorbidities found in existing indices.

1.12 Thesis structure

This is a thesis inclusive of published and submitted-for publication works, and consists of eight chapters (see figure below). Three papers have been published and two have been submitted for review. The first two chapters provide the background with study aims and a description of the data sources and methods used (Chapter 1 includes a published paper). The third chapter provides (1) a description of the outcomes and (2) the association between these outcomes, and comorbidities and socio-demographic variables, in a Victorian study population (Chapter 3 includes a published paper). Chapters 4-6 derive and test injury comorbidity indices for mortality, burden and complications-related outcomes respectively. Chapter 4 includes a published paper, while two papers related to chapters 5 and 6 have been submitted for review. Chapter 7 provides a comparison of the derived indices. The final chapter provides a synthesis of findings including a discussion of the strengths and limitations of the study, contribution to the field of study and future directions.

Figure 1: Thesis structure



Note: Error in following manuscript
Table 1; column 2 row 1 in page 52 should read “Injury populations’ and NOT ‘Noninjury populations’

Annals of Epidemiology 36 (2019) 5–14

Contents lists available at ScienceDirect

Annals of Epidemiology

Review article

Effect of comorbidity on injury outcomes: a review of existing indices

D. Tharanga Fernando, BSc [a,*], Janneke Berecki-Gisolf, PhD [a], Stuart Newstead, BSc (Hons), MSc, PhD, AStat [a], Zahid Ansari, PhD, MS, MPH, MBBS [b]

[a] Monash University Accident Research Centre, Victoria, Australia
[b] Health Intelligence Unit, Victorian Agency for Health Information, Melbourne, Victoria, Australia

ARTICLE INFO

Article history:
Received 12 February 2019
Accepted 16 June 2019
Available online 21 June 2019

Keywords:
Chronic disease
Trauma
Charlson
Comorbidity
Elixhauser
Index
Injury
Outcome

ABSTRACT

Purpose: Accounting for comorbidity in predicting outcomes for patients is vital in clinical care, epidemiological research, and health service planning. The aim of this study was to review published literature to compare the performance of existing comorbidity indices and their use in injury populations.
Methods: A thematic literature search for comorbidity indices and/or injury outcomes was conducted. Methods, results, and recommendations from selected articles were abstracted, documented, and compared; comparisons of results were made in terms of the indices' ability to predict outcomes, using the C-statistic, R^2, and odds ratios.
Results: Fifty-two articles relating to the derivation and/or validation of comorbidity measures were found. The most commonly used measures were the Charlson Comorbidity Index (CCI) and the Elixhauser Comorbidity Measure (ECM). The ECM was found to outperform the CCI in terms of predictive ability, although the CCI was more widely used. Derivation of study-specific weights to the CCI added more predictive power to the index.
Conclusions: Existing literature that compared the predictive abilities of the ECM and CCI favors the ECM. This literature review did not identify a measure specifically designed for general injury populations. Development of an injury-specific comorbidity measure will be timely and assist future research in injury epidemiology.

Introduction

Injury and comorbidity are both associated with adverse health outcomes such as mortality, hospital stay, and use of critical health care services. Accounting for comorbidity will affect a patient's natural clinical course and change the expected outcomes compared with nonconsideration of comorbidity [1]. Comorbidity also plays a vital role in epidemiological research (e.g., in calculating mortality rates or fatality rates for a specific condition) and health and social services planning (compounding effects of comorbidity can inflate resource needs) [1,2].

Both injury and chronic noncommunicable disease (NCD) have been recognized globally as major sources of disease burden, resulting in mortality, loss of functional health, disability in individuals, and costs to health and social service systems. The Global Burden of Disease (GBD) Report—2004 Update [3] showed that NCDs accounted for nearly half of the GBD among all age groups in low- and middle-income countries, and this proportion was much greater in high-income countries. Another GBD report stated that NCDs accounted for 71.3% of deaths globally in 2015 and injuries accounted for 8.5% of deaths [4]. In certain patients, mostly older adults, injury and chronic NCDs are likely to co-occur, with co-occurrence of chronic disease increasing the likelihood of adverse injury burden and mortality outcomes. This substantiates the need for appropriately quantifying comorbidity in establishing prognostic outcomes for injury patients.

To quantify the effect of comorbid conditions, a comorbidity index can be used. A comorbidity index can be used to predict outcomes for patients or adjust for the presence of these conditions in other research and clinical care. A review of these measures,

The study was approved by the Monash University Human Research Ethics Committee (Project no: 1256). The study was literature based and the research is low risk in that there was no discomfort or risk of harm to the participants.

The data that support the findings of this study were accessed from publicly available publications databases and can be accessed via the relevant websites.

The authors declare that they have no competing interests, financially, or otherwise.

* Corresponding author. Monash University Accident Research Centre, Monash University, Clayton Campus, 21 Alliance Lane, Clayton, Victoria 3800, Australia. Tel.: +61-3-9905 1805.
E-mail address: tara.fernando@monash.edu (D.T. Fernando).

https://doi.org/10.1016/j.annepidem.2019.06.004
1047-2797/© 2019 Published by Elsevier Inc.

especially those used in injury settings, will be informative for injury epidemiology. Measures that are adequate and appropriate in quantifying the effect of comorbidity on health outcomes for injury patients will be beneficial in clinical settings, epidemiological research, and health care planning.

Two systematic reviews have been conducted to date, to evaluate the performance of some of the existing comorbidity indices [5,6]. These two reviews, however, did not evaluate this from an injury perspective. The presence of comorbidities varies between injury and noninjury patients [7,8] and comorbidities may not be the key predictors of outcomes for injury patients [9]. Mortality Risk Score for Trauma (MoRT) was an injury-specific comorbidity index derived by Thompson et al. in 2010 [10]. This was based on a cohort of serious injury patients. Serious injury patients account for around 15% of all injury patients [11], and therefore, the MoRT needs further validation to be considered robust for use in general injury populations. Hence, it is still not clear if a specific comorbidity index needs to be derived for use in this population. A preliminary assessment of existing comorbidity measures and their use and utility in injury populations will shed light on their capabilities to account for comorbidities in predicting outcomes and inform if there should be a need for a more specific index for injury patients.

A narrative review of published research was conducted to summarize existing comorbidity measures (indices and alternatives) that have been commonly used to adjust for or test the effect of co-occurring chronic conditions on outcomes. The aim was to assess the capabilities of these measures to predict outcomes for general medical patients and more specifically, for injury patients.

The focus of this review was on commonly assessed health outcomes such as mortality [10,12–15], development of complications [15], additional use of critical care services such as intensive care unit (ICU) stay and mechanical ventilator (MV) use [16], need for long-term nursing care [16], extended length of hospital stay [14], increased likelihood of readmission to hospital [14], and costs [17].

The aim of this study was to review past literature to (1) describe published indices and their evolution, (2) assess the overall performance of the existing main comorbidity indices in terms of predicting health outcomes, and (3) explore their use in injury populations.

The study was approved by the Monash University Human Research Ethics Committee.

Materials and methods

Search strategy

The literature search was conducted using Google, Google Scholar, PubMed, and the Monash University Library (with access to over 4 million articles via platforms such as Ovid) between September 2016 and August 2017. The following terms and their derivations were used to search titles and contents: injury, outcome, comorbidity, pre-existing condition, comorbidity index, Charlson index, Elixhauser, and outcome-related terms such as death, mortality, readmissions, length of stay (LOS), complications, cost, ICU, ventilator, and discharge destination, with the term comorbidity. PubMed was also searched using the medical subject headings (MeSH) terms "comorbidity" and the selected outcome terms as a double check.

Inclusion/exclusion of literature

After an initial screening of abstracts, journal articles relating to development and validation of comorbidity indices (such as the Charlson Comorbidity Index [CCI] and Elixhauser Comorbidity Measure [ECM]) or other measures such as the count of comorbidities, presence/absence of certain comorbidities, or the presence of at least one comorbidity were retained. Articles relating to the development and/or validation of other comorbidity measures such as medication-based indices (chronic disease score and RxRisk) and ICU scoring systems that use severity of diseases classifications (e.g., acute physiology and chronic health evaluation II, simplified acute physiology score II) were excluded. The aforementioned data sources were less commonly available compared with hospital admission administrative data, and this review was more focused toward comorbidity indices that can be applied to the latter form of data. The literature retained for further review were limited to those related to specific injury outcomes such as in-hospital death, mortality, readmissions, LOS, complications, cost, ICU, and MV use and discharge destination. Two systematic literature reviews were also used to identify relevant literature and compare conclusions. Key literature referred to in the chosen articles if it was not picked up initially was included for review. Articles were organized by themes, (1) outcome being studied and (2) study population (injury vs. noninjury), and ordered chronologically in terms of published year.

Data extraction and reporting

Data were abstracted using a tailored data collection form. Abstracted data included information on the study population, comorbidity measure, data source, health outcome measure, predictive ability (C-statistics, R^2, and odds ratios) and final recommendations. The C-statistic measures the ability to discriminate those with and without the outcome, using the area under the receiver operating characteristic curve. The C-statistic ranges from 0 to 1 where 0.5–0.7 represents poor discrimination and anything greater than that considered good discrimination: the larger the C-statistic, the better the predictive ability of the model. Furthermore, using the extracted information and chronologically ordering them based on the studies from which they were sourced, flow charts were drawn to understand the evolution of the widely used comorbidity indices. The extracted information was also tabulated (1) by the more commonly used comorbidity indexes, outcome measures, and predictive ability and (2) by type of comorbidity measures and their use in injury outcome studies. The derivation and use of empirical weights for the commonly used indices were also reviewed.

Results

Abstracts of 188 articles, including two systematic literature reviews pertaining to comorbidity index validation, were screened and 36 were found to derive or validate comorbidity measures and were retained for further review. An additional fourteen articles identified in the two systematic reviews were also retained. Eighteen from the total of 50 articles were based on injury populations. Figure 1.

Main comorbidity indices and their evolution

The most commonly used measures for quantifying comorbidity were (1) the presence of at least one comorbidity; (2) the count of comorbidities; (3) CCI and its variations; and (4) the ECM and its updates.

Charlson Comorbidity Index and Elixhauser Comorbidity Measure

This review focuses on the two indices most commonly used and evaluated for performance, namely the CCI [18] and the ECM

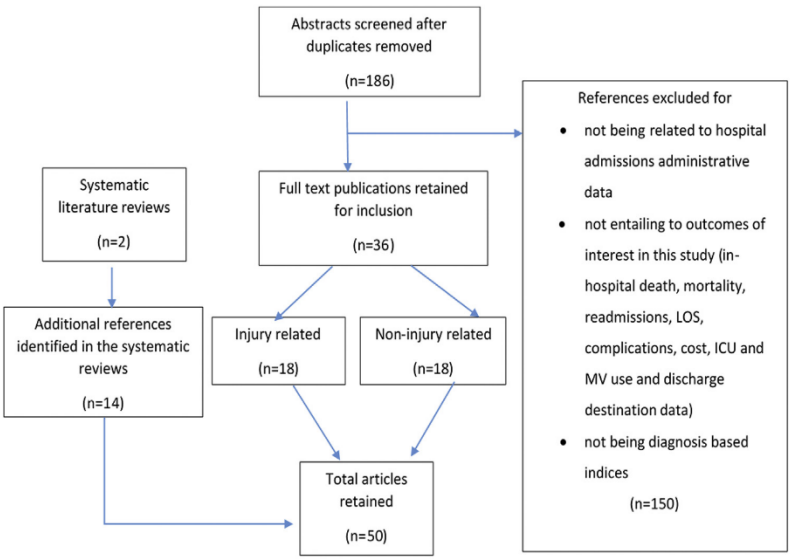


Fig. 1. Flow chart representing the article selection process for this study.

[19]. Both indices are diagnosis-based and are derived from a list of comorbidities (19 comorbidities for the CCI and 30 for the ECM), which are related to a particular health outcome. Figure 2 shows the evolution of these two comorbidity indicators since the early 80s (starting with the initial development of the CCI). The most recent update to the CCI is the new weights derived by Quan et al. in 2011 for twelve comorbid conditions, and for the ECM, it is the weighted score derived by van Walraven et al. in 2009 for twenty-one conditions.

The original ECM used a binary representation of the presence of each considered comorbidity as its measure, whereas the original CCI allocated a weight to each comorbidity and calculated a weighted summed score as the index. The CCI was developed in 1987 using a general cohort of patients admitted to a hospital during a one-month period and then followed up over a course of one year to assess mortality [18]. According to Google Scholar, the CCI has also been cited 26,353 times (9 October 2018) by papers that developed indices as well as those that used the index. The ECM developed in 1998 [19] identified a set of 30 distinct comorbidity groups based on the International Classification of Diseases, Ninth Revision, Clinical Modification codes. The ECM and its variations have all been described as good predictors for in-hospital death [5,20,21].

Seven of the 50 studies used both the CCI and ECM, 3 studies used only the ECM, and 26 studies used only the CCI, whereas 12 used other measures such as the count of or the presence of at least one condition. The CCI and the ECM are discussed in detail next.

Studies that derived empirical weights

Some studies in the past derived empirical weights for comorbid conditions using the CCI list and/or conditions specific to the study population. All of them concluded that study-specific weights outperformed the original CCI weights for assessing mortality outcomes [26,30–33], while Holman et al. (2005) further concluded that, although the empirical weights outperformed the original CCI weights, the ability to predict 30-day readmission and LOS was poor [32]. A comparison of the original CCI weights and the Quan updates of 2011 revealed that conditions such as peptic ulcer disease appear to have no impact on 1-y mortality, whereas conditions such as HIV/AIDS, renal disease, and diabetes have relatively lower impact than they used to, and liver diseases and dementia have acquired relatively higher weights in the updates [29]. These changes could partly be attributed to advances in medical science and changes in disease epidemiology and in part to improvements in comorbidity recording in administrative data sets over time. This emphasizes the need for updating comorbidity measures to select conditions relevant to a specific population and allocating weights that are currently appropriate.

Assessing the overall performance of the main indices in terms of predicting outcomes

Articles that used the CCI and ECM and their variations and updates in quantifying comorbidity are presented in Table 1. The performance of the CCI (and its variations) and the ECM (and its variations) in terms of their ability to predict outcomes are presented for noninjury and injury populations, respectively. The table presents results of studies evaluating the index admission and excludes results of lookback periods. Studies that conclude good predictive ability either found a significant gain in the C-statistic [37,41,44] or R^2 [48] when moving from the baseline model to a model that includes a comorbidity indicator, or found an odds ratios $\geq$1.3 [40,52]. Some of the studies did not discuss this change, instead drew conclusions based on the overall C-statistic. They concluded good predictive ability if the C-statistic for the model with the comorbidity indicator was $\geq$0.7 [20,21,27–29,43], whereas those concluding a weak predictive power of the index found the C-statistic to be in the range of 0.5–0.7 [42]. Li et al. (2010) (validated both CCI and ECM) and Holman et al. (2005) (validated CCI) made no specific conclusion of the predictive ability of the indices they tested, but the C-statistic was less than 0.7, which implies weak predictive power. It should be noted that a measure such as the C-statistic is highly dependent on the study population. It is also dependent on the model adjustment for other variables; that is, the number and type of model covariates drive the C-statistic, and therefore, C-statistics from different studies are not always comparable. A number of studies used the CCI for adjusting for comorbidity in modeling the effect of other variables on health outcomes (e.g., effect of injury on long-term mortality,

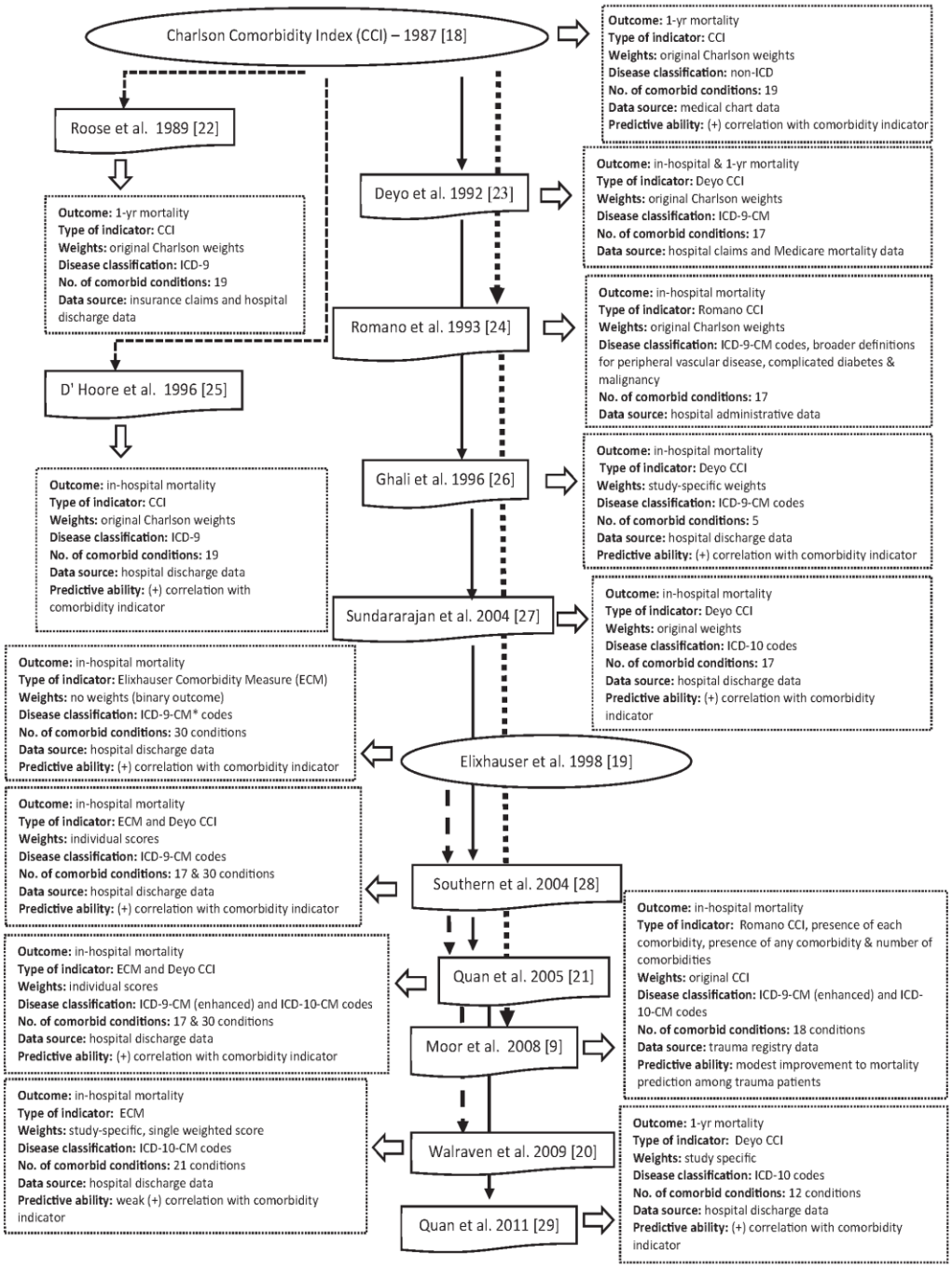


Fig. 2. Evolution of comorbidity indices for short-term mortality [9,18–29].

adjusted for pre-existing comorbidity [8]). For the purposes of this review, they have not been included, as this review focused on establishing the effect of comorbidity on the outcomes rather than adjusting for them. One such study [Kuwabara et al. (2010)] [51] was retained as it was based on an injury population and looked at LOS and costs; such outcomes were not often assessed among injury populations.

The CCI and its variations have been used more often than the ECM (Table 1). Eight studies that compared the performance of the CCI and ECM concluded in favor of the ECM for predictive ability [20,28,35,38,39,42,43,50], which is similar to conclusions drawn by Yurkovich et al. [5]. Studies that found the ECM to perform better than the CCI maintained that comorbidities have independent effects on outcomes and they differ for patient groups [19,24],

Table 1
Performance of existing comorbidity indices for selected outcomes among injury and general patient populations

Outcome measure	Noninjury populations				
	Article	Comorbidity measure	Prediction ability basis	Value of statistic	Author conclusion on predictive ability
In-hospital death	Librero et al. (1999) [34]	CCI (OA)	Standardized-death-rate increment with CCI	Not available	Good
	Stukenborg et al. (2001) [35] ‡,§	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01–0.04 (C-statistic = 0.61–0.72)	Weak
	Stukenborg et al. (2001) [35] ‡,§	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.07–0.09 (C-statistic = 0.66–0.77)	Weak, but better than the CCI
	Sundararajan et al. (2004) [27]	CCI (OA)	C-statistic	0.86	Good
	Southern et al. (2004) [28] ‡	CCI (OA)	C-statistic	0.7	Good
	Southern et al. (2004) [28] ‡	ECM (OA)	C-statistic	0.79	Good and better than the CCI
	Quan et al. (2005) [21]	CCI (OA)	C-statistic	0.86	Good
	Quan et al. (2005) [21]	ECM (OA)	C-statistic	0.87	Good
	Nuttall et al. (2005) [36] ‖	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.02 and 0.04 (C-statistic = 0.71 and 0.73)	Weak
	Zhu and Hill (2008) [37]	ECM (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.14 (C-statistic = 0.72)	Good
	van Walraven et al. (2009) [20] ‡	CCI (OA)	C-statistic	0.75	Good
	van Walraven et al. (2009) [20] ‡	ECM (U)	C-statistic	0.76	Good and better than the CCI
	Li et al. (2010) [38] ‡	CCI (OA)	C-statistic	0.65	No specific conclusion
	Li et al. (2010) [38] ‡	ECM(OA)	C-statistic	0.76	Better than the CCI
	Yu-Tseng et al. (2010) [39] ‡,¶	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.01 (C-statistic = 0.71 and 0.71)	Weak
	Yu-Tseng et al. (2010) [39] ‡,¶	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.041 (C-statistic = 0.74 and 0.74)	Weak, but better than the CCI
	Quan et al. (2011) [29]	CCI (OA)	C-statistic	0.88	Good
	Quan et al. (2011) [29]	CCI (U)	C-statistic	0.88	Good and similar predictive ability to the original CCI
1-y mortality	Goldstein et al. (2004) [40]	CCI (OA)	Statistically significant gain in odds of outcome from model with CCI <2 to CCI >2	OR = 1.72	Good
	Holman et al. (2005) [32] #	CCI (OA)	C-statistic	0.88 and 0.74	No specific conclusion
	Preen et al.(2006) [41] **	CCI (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.05 and 0.06 (C-statistic = 0.89 and 0.92)	Good
	Livingston EH (2007) [42] ‡	CCI (OA)	C-statistic	0.52	Weak
	Livingston EH (2007) [42] ‡,††	ECM (OA)	C-statistic	0.72	Good and better than the CCI
	Yu-Tseng et al. (2010) [39] ‡,¶	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.02 (C-statistic = 0.75 and 0.68)	Weak
	Yu-Tseng et al. (2010) [39] ‡,¶	ECM (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.03 (C-statistic = 0.77 and 0.70)	Weak, but better than the CCI
	Mnatzaganian et al. (2011) [43] ‡	CCI (OA)	C-statistic	0.72	Good
	Mnatzaganian et al. (2011) [43] ‡	ECM (OA)	C-statistic	0.75	Good and better than the CCI
	Quan et al. (2011) [29]	CCI (OA)	C-statistic	0.89	Good
	Quan et al. (2011) [29]	CCI (U)	C-statistic	0.90	Good and similar predictive ability to the original CCI
	Stavem et al. (2017) [44]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.66 (C-statistic = 0.78)	Good
Readmission within 30 d	Librero et al. (1999) [34]	CCI (OA)	Standardized-readmission-rate increment with CCI	NA	Good
	Parker et al. (2003) [45]	CCI (OA)	Wald X^2	$P < .0001$	Good
	Holman et al. (2005) [32] #	CCI (OA)	C-statistic	0.67 and 0.61	No specific conclusion
	Preen et al.(2006) [41] **	CCI (OA)	Statistically significant gain in C-statistic from baseline model to model with comorbidity added	0.03 and 0.02 (C-statistic = 0.64 and 0.62)	Weak
LOS	Librero et al. (1999) [34]	CCI (OA)	Standardized LOS increment with CCI	NA	Good
	Melfi et al. (1995) [46]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 (C-statistic = 0.65)	Weak
	Parker et al. (2003) [45]	CCI (OA)	F-statistic	$P < .0001$	Good
	Holman et al. (2005) [32] #	CCI (OA)	R^2	0.17 and 0.03	No specific conclusion
	Atalay et al. (2009) [47]	CCI (OA)	X^2	NA	Weak

(*continued on next page*)

Table 1 (*continued*)

Outcome measure	Noninjury populations				
	Article	Comorbidity measure	Prediction ability basis	Value of statistic	Author conclusion on predictive ability
			Injury populations		
In-hospital death	Gabbe et al. (2005) [13]	CCI (OA)	Gain in C-statistic from baseline model (including injury severity) to model with comorbidity added	0.03 (C-statistic = 0.86)	Weak
	Moor et al. (2008) [9] *	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.00 (C-statistic = 0.94)	Weak
	Thompson et al. (2012) [48]	ECM (OA)	C-statistic	0.47	Weak
	Neuhaus et al. (2013) [49]	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.62 (C-statistic = 0.77)	Good
	Neuhaus et al. (2013) [49]	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.63 (C-statistic = 0.77)	Good
	Toson et al. (2015) [14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.11 and 0.09 (C-statistic = 0.73 and 0.72)	Good
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.07 (C-statistic = 0.70)	Good
1-y mortality	Kurichi et al. (2007)[50] ‡,§§	CCI (OA)	C-statistic	0.65–0.68	Weak
	Kurichi et al. (2007)[50] ‡,§§	ECM (OA)	C-statistic	0.69–0.70	Weak, but better than CCI
	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.06 and 0.16 (C-statistic = 0.69 and 0.71)	Good
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.08 (C-statistic = 0.71)	Good
Readmission within 30 d	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in C-statistic from baseline model to model with comorbidity added	0.01 and 0.01 (C-statistic = 0.55 and 0.55)	Weak
	Toson et al. (2015)[14] †	CCI (U)	Gain in C-statistic from baseline model to model with comorbidity added	0.00 (C-statistic = 0.54)	Weak
LOS	Kuwabara et al. (2010)[51] ‖‖	CCI (OA)	Beta coefficient for log LOS	0.09 and 0.12	Good
	Thompson et al. (2012)[48]	ECM (OA)	Gain in R^2 from baseline model to model with comorbidity added	Values not provided	Weak
	Toson et al. (2015)[14] †,‡‡	CCI (OA)	Gain in R^2 from baseline model to model with comorbidity added	0.00 & 0.01 (R^2 = 0.01 and 0.01)	Weak
	Toson et al. (2015)[14] †	CCI (U)	Gain in R^2 from baseline model to model with comorbidity added	0.01 (R^2 = 0.01)	Weak
Discharge destination	Chen et al. (2012)[52]	CCI (OA)	Significant gain in odds of outcome from model with CCI <2 to CCI >2	1.29 < OR < 3.65	Good
Costs	Kuwabara et al. (2010)[51] ‖‖	CCI (OA)	Beta coefficient for log cost	0.08 and 0.12	Good
ICU LOS	Thompson et al. (2012)[48]	ECM (OA)	Gain in R^2 from baseline model to model with comorbidity added	0.04	Good

CCI (OA) = original CCI or adaptation (Deyo/Romano); CCI (U) = updated CCI, weights per Quan et al. (2011); ECM (OA) = ECM or adaptations; ECM (U) = updated ECM with scores per van Walraven et al. (2009).

* Count was better.
† Individual presence was better.
‡ Compared CCI and ECM.
§ C-statistic range provided as study tested the index performance on 5 populations.
‖ C-statistic for the Charlson Deyo and Charlson Dartmouth-Manitoba adaptations.
¶ C-statistic for patients with index disease = acute myocardial infarction and index disease = chronic obstructive pulmonary disease.
\# C-statistic for patients with index disease = asthma and index disease = acute myocardial infarction.
** C-statistic for medical patients and procedural patients.
†† Limited to 5 ECM conditions.
‡‡ Study used two algorithms; Sundararajan (2004) and Quan (2005).
§§ C-statistic range provided as study tested the index performance on 3 populations.
‖‖ CCI reference = 0, beta reported for CCI 1 and CCI > 2.

thereby discouraging the use of summary indices. It should, however, be noted that the ECM requires adjusting for 30 binary parameters. This could result in overfitting, and furthermore, this may be impractical when sample sizes are small, resulting in many empty cells. A weighted index with fewer parameters may be more practicable in small samples. Decisions on which index to use are dependent on the data and objective of the study. Overall, the CCI has been praised for its reliability and good correlation with mortality, whereas the drawbacks are that it is limited to 19 conditions and likely to underdetect nonfatal adverse outcomes [53].

Table 1 also shows that the CCI and ECM have been used more often to assess mortality outcomes than resource use. Fewer studies have validated the CCI and ECM on injury populations than general medical populations. Among injury populations, the count or individual presence of comorbidities performed equally well or outperformed the CCI in terms of predictive ability [9,14] (Table 1). Outcomes such as long-term mortality, use of the ICU and MV, and complications have not been assessed for the effect of comorbidity using these indices; ICU and MV use were commonly assessed using individual disease presence [54–56] (not shown in tables). Studies that used the CCI and ECM for nonmortality-related outcomes such as readmission to hospital, LOS, and costs were also fewer in number than studies of mortality-related outcomes (Table 1).

Use of comorbidity indices in injury populations

This review assessed the use of comorbidity measures in predicting outcomes among injury populations, assessing what measures have been used most frequently and how such measures performed in terms of predictive ability. Studies related to injury populations in general were few compared with the number of studies in general clinical populations as seen in Table 1, although the relative proportions of each study type have not been reported as this was not a systematic review and therefore is not an exhaustive list of studies.

Four studies found the CCI good at predicting outcomes among injury patients [14,49,51,52] (Table 1). Kurichi et al. (2007) compared the CCI and ECM for predicting 1-y mortality among elderly veterans with lower extremity amputations, reporting that the ECM only slightly outperformed the CCI [50], and that overall the indices were weak predictors of the outcome. Moor et al. (2008) concluded that a count of comorbidities was as good as the CCI in quantifying the effect of comorbidity on in-hospital death [9] among high-level trauma patients, whereas Toson et al. (2015) suggested that the individual presence of seventeen CCI conditions was better than the weighted score in predicting mortality [14] among older patients with hip fracture. The latter also concluded that the CCI was not suitable for predicting resource utilization.

Table 2 summarizes some of the studies on injury-specific patient cohorts and the use of comorbidity indicators for predicting outcomes. The general consensus from these studies is that the CCI is a good predictor of mortality but not a good predictor for burden-related outcomes. Conversely, the CCI has been recommended as good at predicting discharge destination and disability outcomes [52,59]. The table also shows the absence of studies assessing the CCI for complications.

Indicators of the individual presence of comorbidities has been found to be equally effective or better at predicting health outcomes compared with the CCI by Moor et al. and Toson et al. [9,14] (Table 2). Overall, among injury patients, age and injury severity were better predictors of outcome than comorbidity measures [10,13,49,51,55]. Validation of the CCI or other comorbidity measures on general injury cohorts was scarce (Table 2).

The only study identified that derived empirical weights for an injury population was by Thompson et al. in 2010 [10]. They derived the MoRT using a cohort of patients with serious injury. The MoRT performed just as well as the CCI in predicting mortality, but better predictive ability was gained by adding age, gender, and injury severity to the model. Injury severity, age, and gender were found to add more predictive power in other studies also [13,49,55]. The MoRT was a more parsimonious index, as it used only six comorbid conditions: severe liver disease, myocardial infarction, cerebrovascular disease, cardiac arrhythmias, dementia, and depression. They concluded that in the context of injury, eliciting information on past comorbidity is not always possible and therefore an index with a fewer number of conditions would be more practical.

Discussion

We studied the performance of existing comorbidity indices in terms of predicting outcomes and explored how they have been used for assessing outcomes among injury patients whose data were often sourced from administrative databases.

This review found that of the diagnosis-based indices, the CCI and ECM were the most commonly used comorbidity measures for predicting outcomes among hospital-admitted patients. These two indices were compared for performance in terms of predictive power: the ECM outperformed the CCI, although the CCI was the more commonly used measure [5,6]. The more common use of the CCI could also be due to the fact that it preceded the ECM and had been around for over 11 y before the ECM. Two adaptations of the CCI are available, namely the Deyo and Romano versions; both of which have been proven to have good predictive ability for mortality by certain studies. Several studies explored the derivation of empirical weights for the Charlson list of conditions as opposed to using the original Charlson weights, which had improved the predictive ability of the index [26,30–33,36]. Weights, however, should be reflective of current medical practice and disease prevalence. Many decades have passed since the development of the CCI and eight years since the latest update by Quan et al. [29]. Although regular updates have been made, the scale in its original form is still commonly used. Due to advances in medical science and changes in chronic disease epidemiology, the derivation of new empirical weights at regular time intervals to reflect current medical advances is justified.

This review has brought to light suboptimal use of general comorbidity measures, for example, the use of older versions rather than the updated CCI in specific injury populations. It also found that injury outcomes research tended to focus on subgroups of populations, such as older age groups or specific-injury groups such as traumatic brain injury or hip fractures; only one study focused on all injury patients [57]. Although most injury outcome studies concluded that injury characteristics and age best predict outcomes [9,12,13,55,57], relevant adjustments for comorbidity improved predictive power and so are still necessary. Therefore, appropriate comorbidity measures are required for this group. The only study we found that derived an index based on empirical weights using an injury population did so to assess mortality outcomes. However, this study was based on a cohort of serious injury patients only [10], and we found no validation studies for this index.

This review also found that specific comorbidity measures have so far not been developed for burden-related outcomes such as LOS, readmission, MV use, ICU stay, costs, and complications among injury or general clinical patients. Development of comorbidity measures relating to burden, mortality, and complications for all injury patients, be they weighted summed scores, individual presence of conditions, counts of comorbidities, or the presence of at least one comorbidity, with conditions significant to the outcome, needs to be explored. Such measures can be utilized in a number of settings; in evaluating and comparing treatments, predicting outcomes, and identifying comorbidities that are relevant to a specific outcome. They are useful in teasing out the risk of outcomes from injury-related processes adjusting for comorbidity which is a competing risk. For example, when assessing the risk of noncancer mortality, a weighted-index adjustment accounts for noncancer (comorbidity-related) mortality, where other methods such as survival analysis would use "competing risks" imposed by comorbidities to assess cancer survival.

This study is not without limitations. First, it was not a systematic literature review, and therefore may have missed relevant literature; although based on the retrieval of relevant publications cited in the captured literature, we believe that key literature has been included. Second, the focus of this review was research that used administrative data for creating and validating comorbidity indices and excluded studies based on medical chart review and self-report. Some studies have found chart reviews to better capture comorbidity, which may improve the predictive ability of indicators [44,64]. Given that other studies have found the contrary, the difference in comorbidity capture may not be significant [65,66]. Both data sources have limitations: self-reporting introduces respondent bias whereas administrative data can lack information on comorbidities not treated or actively observed during the hospital episode [39,41–43,48].

Table 2
Comorbidity measures used in injury studies and details of conclusions drawn by authors

Comorbidity measure	Article	Study population	Conclusion
General injury population			
CCI	Kuwabara et al. (2010)[51]	All injury patients	Higher odds of mortality for higher CCI scores but not so much for LOS; CCI was used to adjust for comorbidity rather than establish association
Count	Morris et al. (1990)[57]	All injury (patients >15 y of age)	Higher number of conditions associated with higher odds of mortality; risk greater among patients with less severe injuries
	Mc Gwin et al. (2004)[12]	All injury (patients >50 y of age)	Higher risk of death for older trauma patients with comorbidity and minor injuries than those without
Individual presence of each condition	Morris et al. (1990)[57]	All injury (patients >15 y of age)	Certain conditions associated with higher odds of mortality
	Bochicchio et al. (2005)[54]	Critically ill trauma patients	Selected conditions, age, and comorbidity associated with LOS, MV use, and mortality. Also supports findings from Mc Gwin et al. that mortality is greatly influenced by the injuries.
	Kao et al. (2006)[55]	Mostly high-level trauma centers	Diabetes is a weak factor in predicting mortality, LOS and ICU stay, whereas age and injury severity are stronger factors
	Ahmad et al. (2007)[56]	All injury	Diabetes mellitus associated with ICU stay, ventilator use, and complications, but not mortality and LOS
Specific injury population			
CCI	Gabbe et al. (2005)[13]	Serious injury	CCI is associated with mortality but does not add more predictive power to models with other predictive variables such as age
	Kurichi et al. (2007)[50]	Elderly veterans with lower extremity amputations	
	CCI was weak at predicting 1-y mortality		
	Camilloni et al. (2008)[58]	Home and road injury (patients >65 y of age)	CCI predicts mortality best among mild and moderately severely injured patients
	Moor et al. (2008)[9]	High level trauma center patients	CCI no better than the count of conditions
	Thompson et al. (2010)[10]	Patients 18–84 y, 3 or higher on the Abbreviated Injury Scale	CCI and MoRT performs equally; better predictability achieved by adding injury severity, age, and gender
	Chen et al. (2012)[52]	Traumatic brain injury patients	CCI predicts discharge destination well
	Neuhaus et al. (2013)[49]	Patients > 18 y with hip fractures	Three forms of the CCI; original 1987 CCI, the 1994 age-adjusted CCI, and the 2011 updated and reweighted CCI. All indices good at predicting mortality after adjusting for age and other variables
	Gabbe et al. (2013)[59]	Orthopedic injury patients after surgery	CCI predicts disability well
	Toson et al. (2015)[14]	Patients > 65 y with hip fractures	CCI, a good predictor for mortality but not resource utilization. Presence of individual conditions better than CCI and a lookback period for comorbidity improves prediction of long-term mortality
Count	Moor et al. (2008)[9]	High-level trauma center patients	CCI no better than count of conditions
	Senn-Reeves and Jenkins (2015)[15]	Patients >15 y with blunt thoracic trauma	Comorbidities associated with complications and discharge destination; used 10 selected comorbidities
Individual presence of each condition	Gabbe et al. (2005)[60]	High-level trauma center patients	Comorbidity not an independent predictor of mortality
	Kurichi et al. (2007)[50]	Elderly veterans with lower extremity amputations	
	ECM was only slightly better than the CCI at predicting 1-y mortality		
	Moor et al. (2008)[9]	High-level trauma center patients	CCI no better than individual disease presence
	Thompson et al. (2012)[61]	Traumatic brain injury patients >55 y of age	ECM poor at predicting in-hospital mortality, and LOS, but a good predictor for ICU LOS
	Lustenberger et al. (2013)[16]	Traumatic brain injury patients	Diabetes mellitus associated with mortality and discharge destination but not ventilator use, ICU stay, or LOS
	Morris et al. (2014)[62]	Admissions after trauma resuscitation	Obstructive pulmonary disease and diabetes mellitus associated with readmission, although the more important predictors were ICU stay and surgical site infections
	Hwabejire et al. (2014)[63]	Patients >90 y of age in a high-level trauma center	Comorbidity has no effect on mortality, based on 6 baseline comorbid conditions
	Toson et al. (2015)[14]	Patients > 65 y of age with hip fractures	CCI good for predicting mortality but not resource utilization. Presence of individual conditions better than CCI and a lookback period for comorbidity improves prediction of long-term mortality

Conclusions

Binary representation of individual comorbidities, such as used in the ECM, outperformed weighted indices and other comorbidity measures in predicting health outcomes as per the studies included in this review. However, the performance ability of an index is dependent on the data, study population, and objectives of the research. The ECM although has not been validated enough on injury populations. Most existing comorbidity indices have proven to be good predictors of mortality outcomes but not of resource use or complications. Weighted indices were found to benefit from regular updating of weights using empirical methods to better represent current health practices. A specific comorbidity index for general injury-populations has not been derived to date. Development of measures to quantify the effect of comorbidity on specific clinical outcomes for general hospital–admitted injury patients is essential for improved quantification of the impacts of comorbidity on health outcomes in future injury epidemiology research. The measures developed should resonate with the present epidemiology of chronic diseases, their clinical relevance, and account for the effects of injury-related and demographic factors associated with outcomes. Such an index will eliminate biases introduced by outdated weights and irrelevant comorbidities found in existing indices.

Acknowledgment

This paper is part of a PhD Thesis which is supported by the Victorian Injury Surveillance Unit funded by the Victorian Government.

Authors' contributions: T.F., J.B., and Z.A. conceived the presented idea. The theory and structure was developed by T.F. and J.B. J.B., S.N., and Z.A. supervised T.F. in producing the findings of this work. All authors read and approved the final manuscript.

References

[1] Feinstein AR. The pre-therapeutic classification of co-morbidity in chronic disease. J Chronic Dis 1970;23(7):455–68.
[2] Valderas JM, Starfield B, Sibbald B, Salisbury C, Roland M. Defining comorbidity: implications for understanding health and health services. Ann Fam Med 2009;7(4):357–63.
[3] World Health Organization. The global burden of disease: 2004 update. Switzerland: WHO; 2008.
[4] Wang H, Naghavi M, Allen C, Barber RM, Bhutta ZA, Carter A, et al. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. Lancet 2016;388(10053):1459–544.
[5] Yurkovich M, Avina-Zubieta JA, Thomas J, Gorenchtein M, Lacaille D. A systematic review identifies valid comorbidity indices derived from administrative health data. J Clin Epidemiol 2015;68(1):3–14.
[6] Sharabiani MTA, Aylin P, Bottle A. Systematic review of comorbidity indices for administrative data. Med Care 2012;50(12):1109–18.
[7] Cameron CM, Purdie DM, Kliewer EV, McClure RJ. Differences in prevalence of pre-existing morbidity between injured and non-injured populations. Bull World Health Organ 2005;83:345+.
[8] Mitchell RJ, Cameron CM, McClure R. Higher mortality risk among injured individuals in a population-based matched cohort study. BMC Public Health 2017;17:150.
[9] Moore L, Lavoie A, Sage NL, Bergeron É, Émond M, Liberman M, et al. Using information on preexisting conditions to predict mortality from traumatic injury. Ann Emerg Med 2008;52(4):356–364.e352.
[10] Thompson HJ, Rivara FP, Nathens A, Wang J, Jurkovich GJ, Mackenzie EJ. Development and validation of the mortality risk for trauma comorbidity index. Ann Surg 2010;252(2):370–5.
[11] AIHW, Pointer SC. Trends in hospitalised injury, Australia 1999–00 to 2014–15 Injury research and statistics series no 110 Cat no INJCAT 190. Canberra: AIHW; 2018.
[12] McGwin Jr G, MacLennan PA, Fife JB, Davis GG, Rue III LW. Preexisting conditions and mortality in older trauma patients. J Trauma Acute Care Surg 2004;56(6):1291–6.
[13] Gabbe BJ, Magtengaard K, Hannaford AP, Cameron PA. Is the Charlson comorbidity index useful for predicting trauma outcomes? Acad Emerg Med 2005;12(4):318–21.
[14] Toson B, Harvey LA, Close JC. The ICD-10 Charlson comorbidity index predicted mortality but not resource utilization following hip fracture. J Clin Epidemiol 2015;68(1):44–51.
[15] Senn-Reeves JN, Jenkins DH. Examining the relationship between preinjury health and injury-related factors to discharge location and risk for injury-associated complications in patients after blunt thoracic trauma: a pilot study. J Trauma Nurs 2015;22(3):136–47.
[16] Lustenberger T, Talving P, Lam L, Inaba K, Bass M, Plurad D, et al. Effect of diabetes mellitus on outcome in patients with traumatic brain injury: a national trauma databank analysis. Brain Inj 2013;27(3):281–5.
[17] Farley JF, Harley CR, Devine JW. A comparison of comorbidity measurements to control for confounding in health outcomes studies. DTIC Document; 2005.
[18] Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis 1987;40(5):373–83.
[19] Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. Med Care 1998;36(1):8–27.
[20] van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. Med Care 2009;47:626–33.
[21] Hude Q, Vijaya S, Patricia H, Andrew F, Bernard B, Jean-Christophe L, et al. Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data. Med Care 2005;43(11):1130–9.
[22] Roos LL, Sharp SM, Cohen MM, Wajda A. Risk adjustment in claims-based research: The search for efficient approaches. J Clin Epidemiol 1989;42(12):1193–206.
[23] Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. J Clin Epidemiol 1992;45(6):613–9.
[24] Romano PS, Roos LL, Jollis JG. Presentation adapting a clinical comorbidity index for use with ICD-9-CM administrative data: differing perspectives. J Clin Epidemiol 1993;46(10):1075–9.
[25] D'Hoore W, Bouckaert A, Tilquin C. Practical considerations on the use of the Charlson comorbidity index with administrative data bases. J Clin Epidemiol 1996;49(12):1429–33.
[26] Ghali WA, Hall RE, Rosen AK, Ash AS, Moskowitz MA. Searching for an improved clinical comorbidity index for use with ICD-9-CM administrative data. J Clin Epidemiol 1996;49(3):273–8.
[27] Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. J Clin Epidemiol 2004;57(12):1288–94.
[28] Southern DA, Quan H, Ghali WA. Comparison of the Elixhauser and Charlson/Deyo methods of comorbidity measurement in administrative data. Med Care 2004;42(4):355–60.
[29] Quan H, Li B, Couris CM, Fushimi K, Graham P, Hider P, et al. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. Am J Epidemiol 2011;173(6):676–82.
[30] Klabunde CN, Potosky AL, Legler JM, Warren JL. Development of a comorbidity index using physician claims data. J Clin Epidemiol 2000;53(12):1258–67.
[31] Martins M, Blais R. Evaluation of comorbidity indices for inpatient mortality prediction models. J Clin Epidemiol 2006;59(7):665–9.
[32] Holman CAJ, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. J Clin Epidemiol 2005;58(10):1006–14.
[33] Schneeweiss S, Wang PS, Avorn J, Glynn RJ. Improved comorbidity adjustment for predicting mortality in Medicare populations. Health Serv Res 2003;38(4):1103–20.
[34] Librero J, Peiró S, Ordiñana R. Chronic comorbidity and outcomes of hospital care: length of stay, mortality, and readmission at 30 and 365 days. J Clin Epidemiol 1999;52(3):171–9.
[35] Stukenborg GJ, Wagner DP, Connors AF. Comparison of the performance of two comorbidity measures, with and without information from prior hospitalizations. Med Care 2001;39(7):727–39.
[36] Nuttall M, van der Meulen J, Emberton M. Charlson scores based on ICD-10 administrative data were valid in assessing comorbidity in patients undergoing urological cancer surgery. J Clin Epidemiol 2006;59(3):265–73.
[37] Zhu H, Hill MD. Stroke: the Elixhauser index comorbidity adjustment in-hospital case fatality. Neurology 2008;71(4):283–7.
[38] Li P, Kim MM, Doshi JA. Comparison of the performance of the CMS Hierarchical Condition Category (CMS-HCC) risk adjuster with the Charlson and Elixhauser comorbidity measures in predicting mortality. BMC Health Serv Res 2010;10:245.
[39] Chu Y-T, Ng Y-Y, Wu S-C. Comparison of different comorbidity measures for use with administrative data in predicting short- and long-term mortality. BMC Health Serv Res 2010;10(1):140.
[40] Goldstein LB, Samsa GP, Matchar DB, Horner RD. Charlson index comorbidity adjustment for ischemic stroke outcome studies. Stroke 2004;35(8):1941–5.
[41] Preen DB, Holman CDAJ, Spilsbury K, Semmens JB, Brameld KJ. Length of comorbidity lookback period affected regression model performance of administrative health data. J Clin Epidemiol 2006;59(9):940–6.
[42] Livingston EH. Development of bariatric surgery-specific risk assessment tool. Surg Obes Relat Dis 2007;3(1):14–20.

[43] Mnatzaganian G, Ryan P, Norman PE, Hiller JE. Accuracy of hospital morbidity data and the performance of comorbidity scores as predictors of mortality. J Clin Epidemiol 2012;65(1):107–15.
[44] Stavem K, Hoel H, Skjaker SA, Haagensen R. Charlson comorbidity index derived from chart review or administrative data: agreement and prediction of mortality in intensive care patients. Clin Epidemiol 2017;9:311–20.
[45] Parker JP, McCombs JS, Graddy EA. Can pharmacy data improve prediction of hospital outcomes? comparisons with a diagnosis-based comorbidity measure. Med Care 2003;41(3):407–19.
[46] Melfi C, Holleman E, Arthur D, Katz B. Selecting a patient characteristics index for the prediction of medical outcomes using administrative claims data. J Clin Epidemiol 1995;48(7):917–26.
[47] Atalay A, Turhan N. Determinants of length of stay in stroke patients: a geriatric rehabilitation unit experience. Int J Rehabil Res 2009;32(1):48–52.
[48] Thompson H, Dikmen S, Temkin N. Prevalence of Comorbidity and its Association with Traumatic Brain Injury and Outcomes in Older Adults. Res Gerontol Nurs 2012;5(1):17–24.
[49] Neuhaus V, King J, Hageman MG, Ring DC. Charlson comorbidity indices and in-hospital deaths in patients with hip fractures. Clin Orthop Relat Res 2013;471(5):1712–9.
[50] Kurichi JE, Stineman MG, Kwong PL, Bates BE, Reker DM. Assessing and using comorbidity measures in elderly veterans with lower extremity amputations. J Gerontol 2007;53(5):255–9.
[51] Kuwabara K, Matsuda S, Imanaka Y, Fushimi K, Hashimoto H, Ishikawa KB, et al. Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database. J Trauma Acute Care Surg 2010;68(2):463–70.
[52] Chen AY, Zagorski B, Parsons D, Vander Laan R, Chan V, Colantonio A. Factors associated with discharge destination from acute care after acquired brain injury in Ontario, Canada. BMC Neurol 2012;12(1):16.
[53] Extermann M. Measuring comorbidity in older cancer patients. Eur J Cancer 2000;36(4):453–71.
[54] Bochicchio GV, Joshi M, Bochicchio K, Shih D, Meyer W, Scalea TM. Incidence and impact of risk factors in critically ill trauma patients. World J Surg 2006;30(1):114–8.
[55] Kao LS, Todd SR, Moore FA. The impact of diabetes on outcome in traumatically injured patients: an analysis of the National Trauma Data Bank. Am J Surg 2006;192(6):710–4.
[56] Ahmad R, Cherry RA, Lendel I, Mauger DT, Service SL, Texter LJ, et al. Increased hospital morbidity among trauma patients with diabetes mellitus compared with age- and injury severity score–matched control subjects. Arch Surg 2007;142(7):613–8.
[57] Morris Jr JA, MacKenzie EJ, Edelstein SL. The effect of preexisting conditions on mortality in trauma patients. JAMA 1990;263(14):1942–6.
[58] Camilloni L, Farchi S, Rossi PG, Chini F, Borgia P. Mortality in elderly injured patients: the role of comorbidities. Int J Inj Contr Saf Promot 2008;15(1):25–31.
[59] Gabbe BJ, Harrison JE, Lyons RA, Edwards ER, Cameron PA. Comparison of measures of comorbidity for predicting disability 12-months post-injury. BMC Health Serv Res 2013;13(1):1.
[60] Gabbe BJ, Cameron PA, Wolfe R, Simpson P, Smith KL, McNeil JJ. Predictors of mortality, length of stay and discharge destination in blunt trauma. ANZ J Surg 2005;75(8):650–6.
[61] Thompson HJ, Weir S, Rivara FP, Wang J, Sullivan SD, Salkever D, et al. Utilization and costs of health care after geriatric traumatic brain injury. J Neurotrauma 2012;29(10):1864–71.
[62] Morris DS, Rohrbach J, Sundaram LMT, Sonnad S, Sarani B, Pascual J, et al. Early hospital readmission in the trauma population: Are the risk factors different? Injury 2014;45(1):56–60.
[63] Hwabejire JO, Kaafarani HA, Lee J, Yeh DD, Fagenholz P, King DR, et al. Patterns of injury, outcomes, and predictors of in-hospital and 1-year mortality in nonagenarian and centenarian trauma patients. JAMA Surg 2014;149(10):1054–9.
[64] Lee DS, Donovan L, Austin PC, Gong Y, Liu PP, Rouleau JL, et al. Comparison of coding of heart failure and comorbidities in administrative and clinical data for use in outcomes research. Med Care 2005;43(2):182–8.
[65] Nguyen TQ, Simpson PM, Braaf SC, Cameron PA, Judson R, Gabbe BJ. Comparison of the performance of mental health, drug and alcohol comorbidities based on ICD-10-AM and medical records for predicting 12-month outcomes in trauma patients. BMC Health Serv Res 2018;18:408.
[66] Price J, Estrada CA, Thompson D. Case study. Am J Med Qual 2003;18(1):38–45.

2 Data sources and methods

The purpose of this thesis was to assess and quantify the association between comorbidities and outcomes among hospital-admitted injury patients. This involved the derivation and validation of comorbidity indices to capture the optimum representation of these associations. An exploratory quantitative analysis of existing hospital admissions data was carried out, with the expectation that the analysis will ultimately aid in establishing generalisable facts about the indices. This chapter entails a justification of the methods used for this study, and provides details about the data sources, case selection, data processing (which includes statistical modelling and significance testing) and a description of the internal and external validations of the comorbidity indices that were carried out.

The methodology used for answering a research question varies depending on the type of study. This study falls under exploratory research; in this particular instance, it attempts to establish associations between dependent and independent variables. This kind of research is often based on a standard methodology that uses sufficiently representative data and classical regression techniques. This holds true especially in research that aims to derive indices such as those proposed in this study [21, 22, 25, 33, 35].

The use of standard and routinely collected hospital-morbidity data such as hospital administrative data, regression analysis and their corresponding statistical tests, are suited for this type of exploratory study. For one, they are reliable (the results are reproduceable), and the other, they are valid. Firstly, they are reproduceable, as they use hospital admissions data (hospital morbidity) which is coded to the commonly used international standards such as the International Statistical Classification of

Diseases and Related Health Problems (ICD); therefore, can be applied to most hospital administrative datasets. Secondly, they are reproduceable as they use *variables* commonly found in such datasets, and thirdly, they employ *methods* that are commonly used in such studies. The results obtained from such analysis is valid, as it corresponds to established methods used for determining statistically significant associations between outcomes and factors.

Finally, in terms of ethical considerations, this study uses pre-existing de-identified data which makes it low risk; there is no discomfort or foreseeable risk of harm to the participants.

A methodological framework is included in Appendix 1.

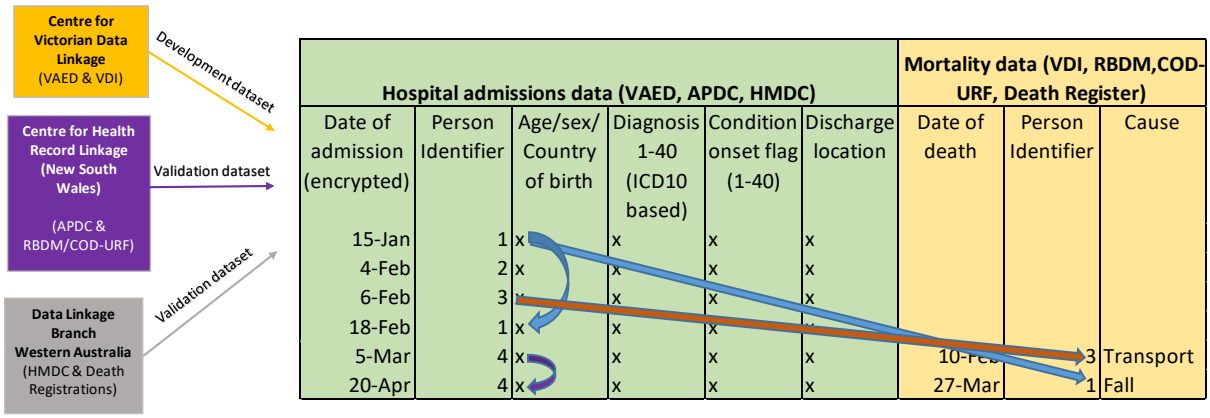
2.1 Data sources

Morbidity data were extracted from the Victorian Admitted Episodes Dataset (VAED) for Victoria, Admitted Patient Data Collection (APDC) for NSW and the Hospital Morbidity Data Collection (HMDC) for WA, all of which contain unit records of all public and private hospital admissions. These datasets include patient demographics, morbidity including external causes, and patient discharge status. The number of diagnosis codes recorded per patient episode varied by state, ranging from 40 in the VAED to 51 in the APDC and 78 in the HMDC. These fields included external cause information that helped identify injury characteristics. In all three hospital datasets, the information in these diagnosis fields were coded to the ICD, Tenth Revision, Australian Modifications (ICD-10-AM) [36].

Mortality data were extracted from the VAED (in-hospital deaths) and the Victorian Death index (VDI) from the Registrar of Births, Deaths and Marriages (RBDM) records in Victoria, APDC, RBDM and COD-URF (Cause of Death – Unit

Record File) in NSW, and HMDC and Death Registrations Database in WA. Treatment costs at hospitals were extracted from the Victorian Cost Data Collection and linked to the VAED for Victoria. Data linkage was conducted by the relevant data linkage body in each State, namely, the Centre for Victorian data linkage (CVDL), Centre for Health Record Linkage (CHeReL) for NSW and the Data Linkage Branch (DLB) for WA. Linkage methods can be found in the manuscripts attached to Chapters 3, 4, 5 and 6. CVDL estimates the false positive rate to be between 0.5% to 1%, and the false negative match rates to be between 1% - 2%. The two rates for the APDC is estimated to be around 0.5% [37]. It is expected that the false negatives in the Western Australian Data Linkage System exceed the number of false positives; the derivation of specific estimates though are not attempted. Figure 2 contains a snapshot of the data sources and an example of data linkage.

Figure 2: Data sources and linkage example



SAS software, Version 9.4 [38] and Stata 14.0 (StataCorp) [39] were used to analyse the data.

2.2 Cohort selection

Sampling was unwarranted as this was a population-based study. Injuries considered for this project do not include medical injury (those that take place in the

context of medical and surgical care). Injury cases were selected using a protocol established for previous national reporting in Australia [40], i.e., records with an injury diagnosis (ICD-10-AM diagnosis code in the range "S00" to "T75" or "T79" in the first appearing diagnosis field). Selected cases were limited to those with an index injury. An ‘index injury’ for this study is the first injury record in the morbidity dataset for a patient during the study period. Records with an admission source indicating a transfer from another hospital or a statistical separation (change in care type within the same hospital) in consecutive records for the same patient were considered to be part of the same episode, until the next record with an admission source indicating otherwise appeared for the patient. The selected patients for each Australian state were those resident in that State.

Two patient cohorts were selected for each state; one for the purposes of observing short-term outcomes such as in-hospital death, complications and burden, and the other for long-term mortality outcomes such as 30-day, 1-year and 5-year mortality, and time until death.

The first cohort consisted of patients with an index injury admission between 01 July 2012 and 30 June 2014 in each state (161,334 patients for Victoria, 233,521 for NSW and 84,877 for WA). Using data linkage (linkage performed using a patient-specific identifier), patients were followed up for all hospital admissions subsequent to their index injury admission for a period of two years from the index injury date within the morbidity dataset for each State.

The second cohort were patients with an index injury admission in the *morbidity data* selected as follows in the states of Victoria and NSW (WA was excluded as data was not available at the time the analysis was carried out): (1) 01 July 2006 to 30 June 2015, followed up till 30 June 2016 in the linked *death data* for Victoria (614,762

patients) and (2) 01 July 2008[1] to 30 June 2015 followed up for one year (705,963 patients) for NSW. The Victorian cohort were followed up for time until death (or end of study period, which ever came first). This is because the study explored the possibility of 5-year and time until death analysis at the start of the project.

2.3 Data preparation for analysis

Below is an explanation of how missing data were treated, exclusion of certain variables and cases, and the coding of outcomes and factors.

2.3.1 Missing data

Both the morbidity and mortality data used in this study were extracted from registries. The main variables of interest (outcomes, injury, socio-demographic and comorbidity data) were coded well and in most instances did not require any imputations for missing data.

2.3.2 Excluded variables

A patient's functional status before and after the injury (variables such as the functional independence measure and resource utilisation groups—activities of daily living) play a role in outcomes. There were uncertainties regarding the completeness of coding in relation to these variables, and therefore were not considered for analysis. Cost data were missing for private hospitals, some public hospitals, and also for certain years in Victoria. Cost data from the other two states were not available for this study, therefore external validations related to costs were not carried out. The method

[1] NSW data does not contain the comorbidity information required for this study prior to 2008.

used to address the missing cost data is detailed in the manuscript attached to Chapter 3.

Certain case selection criteria were used to remove outliers; these can be found in the manuscripts attached to chapters 3, 4, 5 and 6. For example, patients who died within 24-hours, those who stayed longer than 365 days, or were palliative-care patients were excluded when assessing in-hospital death. For comorbidity index derivation for all outcomes, children (aged <15 years) were excluded, as this group is heterogeneous to the rest of the cohort given the low prevalence of comorbidity in the group.

Groupings of certain factor variables were made to be compatible with existing research (such as age groups and injury groups) while certain outcome variables were categorized (binary) or log-transformed for a more sensible analytical approach. The details for these can also be found in the same manuscripts.

2.4 Study variables

The main aim of the thesis was to establish associations between outcomes of hospital-admitted injury patients and comorbidities. As a first step, it was required to identify the outcomes, the comorbidities, and the other factors that may affect the outcomes. Below is a listing of these variables, whereas details of how they were coded can be found in the corresponding chapters (in their attached manuscripts).

2.4.1 Dependent variables (outcomes)

2.4.1.1 Mortality

1. In-hospital death (Chapters 3 & 4)
2. 30-day mortality (Chapters 3 & 4)

3. 1-year mortality (Chapters 3 & 4)
4. 5-year mortality (dropped after initial assessment)
5. Time until death (dropped after initial assessment)

2.4.1.2 Burden

1. Overnight stay (Chapters 3 & 5)
2. LOS (days) (Chapters 3 & 5)
3. Cost (Chapters 3 & 5)
4. All-cause 30-day readmission (post initial discharge) (Chapters 3 & 5)
5. Non-planned 30-day readmission (post initial discharge) (Chapters 3 & 5)
6. Potentially-avoidable 30-day readmission (post initial discharge) (Chapter 3)

2.4.1.3 Complications

1. CHADx-complications (Chapters 3 & 6)
2. ICU stay hours (Chapters 3 & 6)
3. MV hours (Chapters 3 & 6)
4. CCU hours (Chapter 3)

2.4.1.4 Discharge destination *(Chapter 3)*

The CHADx offers a comprehensive classification of hospital-acquired conditions available for use with the ICD-10-AM codes [34]. It is a list of 144 detailed classes and 17 ‘rolled-up” complication groups, mainly used to help hospitals calculate their adverse event rates. Developed in Australia, the main expectation from the

CHADx is to provide a monitoring platform for hospitals on hospital-acquired diagnoses, so the quality of services could be improved. The complications coding for this study was based on the CHADx. The codes can be found on the Australian Commission on Safety and Quality in Health Care website (https://www.safetyandquality.gov.au/publications-and-resources/resource-library/classification-hospital-acquired-diagnoses-chadx-icd-10).

Potentially-avoidable readmissions coding was based on the Striving for Quality Level and analysing of patient expenditures (SQLape) algorithm as published by Halfon et al. (2002) [41] and the SQLape website [42]. They help identify potentially-avoidable readmissions using ICD-10 codes. Some of the recent research has considered assessing potentially-avoidable readmissions using this algorithm and justified its use [43, 44]. The use of the SQLape as a method was justified by its clear and clinically logical criteria, being reproducible and its ability to be applied to large data analysis [43].

Both the CHADx and potentially avoidable readmissions are explained in the manuscript attached to chapter 3.

In the analyses in Chapters 3 – 6, the outcomes were treated as binary (yes / no), count or continuous (non-negative) responses. They are shown below;

1. In-hospital death (binary)
2. 30-day mortality (binary)
3. 1-year mortality (binary)
4. Overnight stay (binary)
5. LOS (days) (count)

6. Cost (continuous)
7. All-cause 30-day readmission (binary)
8. Non-planned 30-day readmission (binary)
9. Potentially-avoidable 30-day readmission (binary)
10. CHADx-complications (count)
11. ICU stay (binary) & hours (continuous)
12. MV use (binary) & hours (continuous)
13. CCU stay (binary)
14. Discharge destination (binary)

2.4.2 Independent variables

Two groups of independent variables were used in this study. The first were the main factors for adjustment in the baseline models, and the second were comorbidities which were the main variables of interest.

2.4.2.1 Main factors

The first group (adjustment factors) consisted of the following:

1. Age
2. Gender
3. Body region
4. Injury type

5. Injury severity (using the International Classification of Disease-based *Injury* Severity Score [*ICISS];* Osler, Rutledge, Deis & Bedrick, 1996 [45])
6. Socio-Economic Indexes For Areas (SEIFA)
7. Geographic region
8. Country of birth

With regards to injury severity, a decision was made to use the ICISS as published by Henley and Harrison (2009) [46]. In calculating the ICISS, each injury was given a severity scoring based on published survival risk ratios (SRR)s. Based on these, a final score was calculated either using the worst injury or the multiplicative effect of all the injuries.

Details of the coding can be found in the paper attached to chapter 3. All independent variables were either received as or re-coded as categorical variables.

2.4.2.2 Comorbidities (main variable of interest)

The identification of comorbidities was based on two methods: (1) using established algorithms such as the CCI and ECM as updated by Quan et al. (2005) [47] and Sundararajan et al. (2004) [48] and (2) searching for additional ICD-10 diseases codes not listed in the above algorithms, with a prevalence of more than 1% in the study population. The latter method revealed that such codes were related to symptoms and complications and not comorbidities, and were excluded from further incorporation in to the analysis. Based on these, 31 comorbidity groups were selected for this study. The ICD-10 codes used for each disease group are listed in Appendix 2. Details of comorbidity prevalence and capture are discussed in Chapter 3.

2.5 Statistical methods

2.5.1 Descriptive analysis

Descriptive analysis was carried out to determine the distribution of the outcomes: in-hospital death, 30-day, 1-year and 5-year mortality, time until death, LOS, critical care services (CCS) use, cost, readmissions and discharge destination. These were described in terms of frequencies and proportions for binary outcomes, means with 95% confidence intervals (CIs), medians with inter-quartile ranges (IQRs) and histograms for continuous and count variables.

2.5.2 Regression analysis

Regression analysis was used to establish associations between independent and dependent variables. Regression analysis is a commonly used method for establishing associations between covariates/factor-variables (independent variables) and outcomes (dependent variables). For ease of use, the independent variables are called 'factors' in the rest of the thesis. Studies that derived comorbidity indices also used regression analysis to derive the indices, and moreover, they used the regression coefficients from their analysis as comorbidity weights. These will be explained further in this chapter.

This study consists of large sample sizes, therefore effect sizes were considered more meaningful than *p* values to establish associations between outcomes and factors [49] although *p*-values were computed.

2.5.2.1 Univariate analysis

Univariate analysis was carried out to establish associations between outcomes and selected factors (i.e., socio-economic, demographic and injury

variables). The associations established were used mainly to identify the factor variables to be included in the multivariable analysis.

Logistic models were run on the binary outcomes, negative binomial models for responses classified as counts, and log-transformed linear models for outcomes classified as continuous variables. Odds ratios (ORs), incident rate ratios (IRRs) and beta coefficients were used to assess the impact of each factor on the outcomes for binary, count and continuous outcomes respectively.

Effect sizes and confidence intervals of the regression coefficients were examined to establish the associations, with an effect size of ± 30% considered as notable. The normative (logical) or largest categories were used as reference groups for regression analysis [49].

Univariate analyses were also carried out to test the associations between pairs of outcomes, even though the focus of this study was to establish associations between outcomes and factors. Most outcomes are likely to occur post hospital-admission, and therefore unlikely to be present at the 'time of' hospital admission. The aim of this research was to quantify comorbidity that helps predict outcomes based on data available at point of hospital admission. These include, socio-demographic factors, injury characteristics and comorbidity, and does not include outcomes. Therefore, the association between outcomes was not pursued beyond establishing the univariate associations.

2.5.2.2 Multivariable analysis

Multivariable regression analysis was carried out to assess the associations between outcomes (dependent variables) and comorbidities (independent variable of interest) while adjusting for socio-demographics and injury factors.

The first step was to build the baseline models. A full model which included, age, gender, body region of injury, injury type, injury severity, SEIFA decile, geographic region and the country of birth as independent variables was fitted with the outcome as the dependent variable. The type of regression model (i.e., logistic, negative binomial and log-transformed linear) was selected based on the response type of the outcome. Using a backward elimination process, one independent socio-demographic or injury characteristic variable was removed at a time and the resulting model compared with the previous model for goodness-of-fit. Due to the data being large-sized, *significance tests* were not meaningful for assessing change in goodness-of-fit for the models; instead the Akaike Information Criterion (AIC) [50] was used to compare between models. A difference of 10 or more between the AIC statistics for two models was considered a meaningful difference in model-fit, which is considered the general cut-off for these comparisons [51]. This elimination process led to identifying the baseline variables that were associated with the outcome.

Once the baseline models were established, comorbidity was added as an independent variable. Comorbidity was added using various forms of quantification. They were the:

1. presence of at least one comorbidity
2. count of comorbidities
3. binary presence of each comorbidity (31 conditions)
4. CCI
5. updated CCI
6. ECM
7. Australian Injury Comorbidity Index (AICI)
8. weighted summed score of the AICI (actual weights)

9. weighted summed score of the AICI (integer weights)

The first three quantifications of comorbidity are straightforward. The CCI, updated CCI and ECM are existing comorbidity measures. The Australian Injury Comorbidity Indices (AICIs) were derived by starting with the binary presence of all 31 comorbidities as a full model. Then, using a backward elimination, one comorbidity was removed at a time and the AICs compared for goodness-of-fit. A difference of less than 10 between two AICs indicates that the model with the additional comorbidity provides no further improvement to the model fit than the one without; therefore, the particular comorbidity is excluded as non-significant to the outcome. The final resultant list of comorbidities for each outcome became the binary injury comorbidity index (namely the AICI) for that outcome.

Interaction effects were assessed for age vs sex, age vs comorbidity and sex vs comorbidity, as these are the likely interactions to be expected. Mediator and moderator effects were considered, but eventually dropped from further assessment as the aim of this study was to derive indices and not about answering a hypothesis.

2.5.2.3 Deriving comorbidity weights

The next step was to derive weighted comorbidity indices. The regression coefficients of the binary comorbidity indices were used to derive comorbidity weights. The resulting coefficients were converted to effect sizes. For logistic regression models, the ORs were used as the weights, the IRRs for the negative binomial models and the exponential of the beta coefficients for the linear regression models. Charlson et al. (1987) found that there was no difference in using either the actual weights or the rounded integers of the weights. Therefore, this study derived weighted summed scores using the actual weights as well as the integers of the weights. The following

rules were applied in allocating weights: the condition was dropped from the weighted index if the effect size was <1.2 (<20%)[2]; 1.2≤ effect size <1.5 (>=20% & <50%) resulted in a score of 1; 1.5≤ effect size <2.5=2; 2.5≤ effect size <3.5=3 and so on. This scoring system is similar to that followed by Charlson et al. [21]. The weights of the resulting comorbidities were then summed to derive the weighted comorbidity indices.

Finally, parsimonious binary comorbidity indices were also derived for each group of outcomes. For example, for mortality, a parsimonious binary index for all mortality was derived using the comorbidities common to all three specific-mortality outcomes (i.e., in-hospital death, 30-day and 1-year mortality). Similarly, a parsimonious index for burden (i.e., for overnight stay, LOS and cost) and readmissions (all-cause and non-planned) were also derived.

2.5.2.4 Significance tests

The relative performance of each comorbidity measure was assessed using the predictive power each adds to the baseline model. The following were used for the three types of regression models:

2.5.2.4.1 Logistic regression

Discrimination (area under the receiver operating characteristic curve (AUROC)) and classification tables were used to assess and compare predictive

[2] Note: effect size cut-off of 20% used for weight calculation in the multivariable regression analysis is different to the effect size of 30% used in the univariate analysis to identify factors associated with outcomes.

powers of regression models. The area under the curve (AUC)[3], ranges from 0 to 1; under 0.7 was considered as representing poor discrimination and anything above that as good discrimination [52]. The significance of differences between AUC statistics were assessed using the CIs; overlapping CIs were considered as an indication of no difference between two AUCs. Classification tables were derived on the basis of maximizing the sensitivity and specificity; setting this as the cut-off point for classifying cases predicted by the models. Tests of proportions were carried out to assess the difference between false negatives obtained using the classification tables, with a significance level of 5%. Sensitivity analysis does not include additional calculations for variables such as age, injury severity etc. as all models are adjusted for these variables. However, their sensitivity is addressed under internal validations (section 2.6).

2.5.2.4.2 Negative binomial regression

McFadden's R^2 statistic was used as an indication of predictive ability of the negative binomial regression models. This is a pseudo R^2, which assesses the ratio of the log likelihood of the fitted model to that of a simple intercept only model as a measure of how much additional information about the data has been captured in the fitted model. Like the classical R^2 measure from the linear model, it has values that range from 0 to 1.

[3] The AUC is also referred to as the C-statistic; the term C- statistic was used in Chapter 1 and the paper attached to chapter 1, as most of the literature reviewed used that term. The rest of the chapters use the term AUC.

2.5.2.4.3 Linear regression

The adjusted-R^2 was used as an indication of the predictive ability of the linear regression models. The R^2 statistics are not ideal representations of predictive capacities of a model, but in the absence of meaningful significance tests, these presented the next best alternative. The main goal of the study was to derive indices that best capture comorbidity in assessing outcomes, therefore using the same R^2 metric for all comorbidity measures was sufficient to compare performances across the measures.

Using these statistics, comparisons were made on the performance of existing comorbidity measures such as the CCI, updated CCI and ECM on predicting outcomes, with the newly derived binary indices (AICIs) and the newly derived weighted comorbidity indices.

2.6 Validations

The aims of the validations were to assess the robustness of the new indices, and to compare with the robustness of existing indices.

2.6.1 Internal validations

The internal validations allowed the assessment of each comorbidity index's performance in patient subgroups. Internal validations were carried out on the CCI, ECM and the AICI using patient subgroups in the Victorian data; i.e., assessed the performance of the AICI compared to the existing CCI and ECM, in terms of explaining the impact of comorbidity on injury outcomes within subgroups.

For the internal validations, patient sub-groups were selected based on demographics and/or injury characteristics. They were children (<15 years), adults (15-24 years), older adults (>= 65 years), males, females, patients with non-severe

injury, severe injury, intracranial injury, hip-fractures (among those aged 45 years and above), blunt trauma and penetrating trauma.

2.6.2 External validations

The external validations allowed the assessment of the indices' generalisability across different demographics and/or different data collections. External validations of the new AICIs were carried out using the full hospital-admitted injury cohorts from the states of NSW and WA.

The method used for validation was similar to that performed for index derivation. The same model structures (terms) that were used in Victoria for the baseline models were refitted on each subgroup and interstate patient cohorts with the addition of the AICI, CCI and ECM separately. The results were compared using either the AUC and false negatives (FNs) for logistic regression models and the R^2 for the negative binomial and linear models.

In conclusion, the justification for the choice of outcomes for this study was that they were most commonly researched outcomes and the choice of comorbidities was based mostly on established work. Given the difficulty to draw reliable conclusions on significance using *p* values due to the large sample problem, the use of effect sizes, AUCs, FNs, AICs and R^2 statistics are justified.

The next chapter is a description of the outcomes, socio-demographics, injury characteristics comorbidities and their associations.

3 Hospital-admitted injury patients - a description of outcomes, socio-demographic and injury characteristics, and comorbidity

This chapter includes a paper which was published in *BMC Public Health*

titled

"Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study".

(attached at the end of the chapter)

Fernando DT, Berecki-Gisolf J, Newstead S & Ansari Z (2019b) [53]

The literature review incorporated in Chapter 1 identified a range of outcomes (and their various measurements) and factors likely to affect such outcomes, for injury and non-injury patients. Using that information, a subset of outcomes (section 1.10.1) were selected for the present study. This chapter contains a description of these selected outcomes by their various methods of measurement, and factors likely to be associated with them in a hospital-admitted injury population. These measures include aspects of burden, complications and mortality (short- and long-term). Such outcomes are most likely affected by the injury characteristics, while socio-demographic factors and comorbidity are also likely to play an important role [1].

The specific research questions addressed are (from the subsidiary questions in Chapter 1):

Based on the analysis of Victorian data:

a. How can injury outcomes best be quantified?

b. How do comorbidities affect the outcomes of hospitalised injury patients?

c. Can the effect of comorbidity be generalised across a range of outcomes?

3.1 Summary

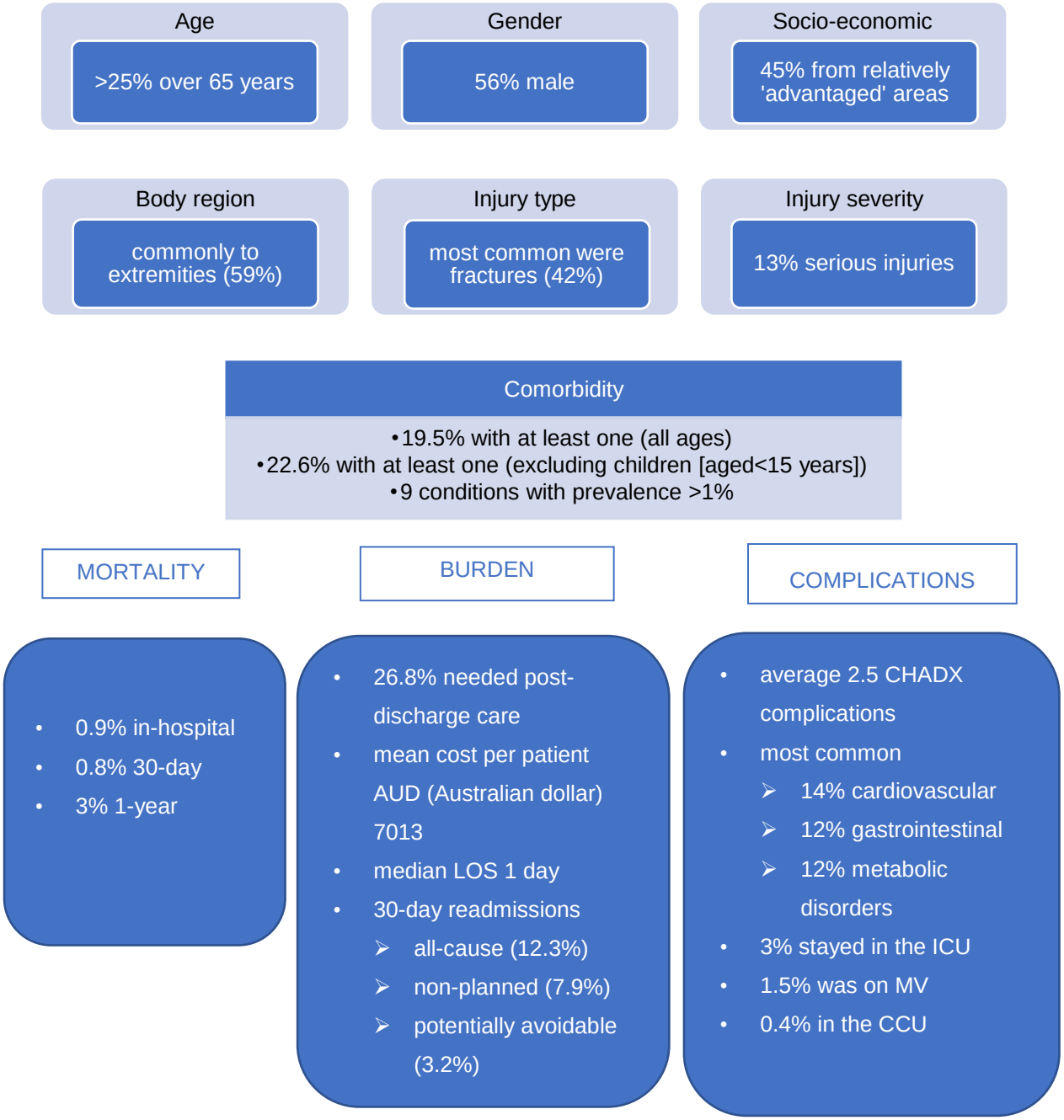
Key summary statistics are presented in section 3.1.1. Detailed results for burden, complications and in-hospital death outcomes can be found in the publication attached to this chapter. The results for 30-day and 1-year mortality analysis were published at the *Annals of Emergency Medicine* as a paper titled “The Australian Injury Comorbidity Index (AICI) to predict mortality” [54]. It must be noted here that rresults of the 5-year mortality and time until death analyses are not shown in any part of this thesis as these outcomes were eventually dropped from further evaluation for reasons explained below.

Based on this initial analysis, 5 of the 16 outcome measures were dropped from analyses in the upcoming chapters; these were: 5-year mortality, survival time, potentially-avoidable readmission, cardiac care unit (CCU) stay and discharge destination. Five-year mortality was dropped due to the outcome being irrelevant for deriving comorbidity indices; long-term survival is unlikely to be dependent on comorbidity when outcomes are assessed for injury. Time until death was dropped due to the insufficient number of deaths in the population to run a survival analysis with meaningful results. The identification of potentially-avoidable readmissions was insufficiently reliable to proceed further (see attached paper for details on this limitation). CCU stay occurred in a very small proportion of patients and therefore dropped from index derivation. Discharge destination would also be dependent on the injury over comorbidity; therefore, not pursued further for deriving comorbidity indices.

This analysis overall assisted in identifying outcomes that were reliably measurable using linked hospital morbidity and mortality data. The outcomes were: in-hospital death, 30-day and 1-year mortality, LOS, costs, all-cause and non-planned

30-day readmissions, discharge destination, ICU stay, CCU stay, mechanical ventilator (MV) use and hospital-acquired complications (CHADx complications). This provides the answer to question a: how can injury outcomes best be quantified (using hospital administrative databases such as the VAED)?

3.1.1 Factors, outcomes and comorbidities at a glance



3.1.2 Associations between factors and outcomes

This study found that the likelihood of all adverse outcomes increased with the increase in the number of comorbidities, which provides the answer to question b: how do comorbidities affect the outcomes of hospitalised injury patients? It was also seen that the likelihood of in-hospital death was three times greater for those with two comorbidities than for patients with one comorbidity, whereas if the focus was a readmission outcome, that likelihood was less than doubled (Table 3 in attached paper). This shows that the effect sizes for the relationship between comorbidities and outcomes vary by outcome and cannot be considered equal, providing the answer to question c: can the effect of comorbidity be generalised across a range of outcomes in terms of the count of comorbidities?

3.2 Implications

The finding that the effect of comorbidity cannot be generalised across all outcomes, as reported in this chapter, has been suggested in previous research [26-32]. It implies that when deriving measures to quantify the association between comorbidity and outcomes, each outcome should be treated individually, and subsequently, assessments should be made as to whether these associations can be generalised across outcomes. The next three chapters focus on the derivation of comorbidity indices for mortality, burden and in-hospital complications separately. The associations established between outcomes and factors in this chapter provide the baseline for building models that have been used for deriving the comorbidity indices.

Fernando *et al. BMC Public Health* (2019) 19:798
https://doi.org/10.1186/s12889-019-7080-y

BMC Public Health

RESEARCH ARTICLE Open Access

Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study

Dasamal Tharanga Fernando[1*], Janneke Berecki-Gisolf[1], Stuart Newstead[1] and Zahid Ansari[2]

Abstract

Background: A wide range of outcome measures can be calculated for hospital-treated injury patients. These include mortality, use of critical care services, complications, length of stay, treatment costs, readmission and nursing care after discharge. Each address different aspects and phases of injury recovery and can yield vastly different results. This study aims to: (1) measure and report this range of outcomes in hospital-treated injury patients in a defined population; and (2) describe the associations between injury characteristics, socio-demographics and comorbidities and the various outcomes.

Methods: A retrospective analysis was conducted of injury-related hospital admissions from July 2012 to June 2014 (152,835 patients) in Victoria, Australia. The admission records were linked within the dataset, enabling follow-up, to assess the outcomes of in-hospital death, burden, complications and 30-day readmissions. Associations between factors and outcomes were determined using univariate regression analysis.

Results: The proportion of patients who died in hospital was 0.9%, while 26.8% needed post-discharge care. On average patients had 2.4 complications (confidence interval (CI) 2.4–2.5) related to their initial injury, the mean cost of treating a patient was Australian dollars 7013 (CI 6929–7096) and the median length of stay was one day (inter quartile range 1–3). Intensive-care-unit-stay was recorded in 3% of the patients. All-cause 30-day readmissions occurred in 12.3%, non-planned 30-day readmissions in 7.9%, while potentially avoidable 30-day readmissions were observed in 3.2% of the patients. Increasing age was associated with all outcomes. The need for care post-discharge from hospital was highest among children and the oldest age group (85 years and over). Injury severity was associated with all adverse outcomes. Increasing number of comorbidities increased the likelihood of all outcomes. Overall, outcomes are shown to differ by age, gender, comorbidities, body region injured, injury type and injury severity, and to a lesser extent by socio-economic areas.

Conclusions: Outcomes and risk factors differ depending on the outcome measured, and the method used for measuring the outcome. Similar outcomes measured in different ways produces varying results. Data linkage has provided a valuable platform for a comprehensive overview of outcomes, which can help design and target secondary and tertiary preventive measures.

Keywords: Burden, Complications, Death, Hospital-admitted, Injury, Linkage, Outcome, Readmission

* Correspondence: tara.fernando@monash.edu
[1]Monash University Accident Research Centre, Monash University, Clayton Campus, 21 Alliance Lane, Clayton, Victoria 3800, Australia
Full list of author information is available at the end of the article

Background

Injury hospitalisation rates have risen in Australia at 1% per year [1, 2] and in 2011, injury was ranked fifth among the most common causes for disease burden; burden was measured as years lost to premature death or living with illness [3]. Injury can be life-threatening, lead to permanent disability, or impair functional outcomes, resulting in poor quality of life. Adverse injury outcomes include accelerated mortality [4–8], development of complications [9–11], additional use of critical care services (CCS) during hospital stay [10, 12–14], need for long-term nursing care post-hospital-discharge [12, 15, 16], extended length of hospital stay (LOS) [8, 17], increased hospital costs [14, 18] and increased likelihood of readmission to hospital (post-discharge for an index condition) [8, 19].

Various methods exist for measuring each of these injury outcomes. Mortality following hospitalisation can be examined at different time points, including death in hospital [4, 5, 17, 20–22], 30-day mortality [23], death within one year [7, 17, 22] or time until death [24, 25], while readmission can be measured as all-cause [8, 26], non-planned [19, 27] or potentially avoidable [26, 28–30]. Similarly, complications can be identified as the leading adverse event (using a hierarchy of codes for ranking importance) [31], the presence of at least one adverse event [32] or count of multiple adverse events [33]. Complications can also be distinguished as hospital acquired [32, 34] or non-hospital acquired (i.e., complications related to the injury or comorbidity). Injury outcomes can vary depending on the aspect studied: for example, *all-cause* 30-day readmissions are much more common than *potentially avoidable* 30-day readmissions [26]. Similarly, *in-hospital* mortality is much lower than *one-year* mortality [7, 17, 22]. Although each of these listed measures are quantifications of injury outcomes, they are rarely used in combination and compared, even though outcomes (and risk factors for adverse outcomes) can differ based on which measure is used. Reporting of injury outcomes and risk factors will help with design of injury outcome studies, and interpretation and comparison of published injury outcomes studies conducted in similar settings.

Numerous studies have established that outcomes are associated with factors such as age [5, 8, 11, 35] and gender [23, 36]. Among injury patients, injury mechanism [4, 6, 11, 14] and severity [4, 6, 14, 37] play a key role. The presence of pre-existing chronic diseases/conditions (comorbidities) can also have negative effects on injury outcomes [5–8, 12, 38, 39].

In 2015–16, there were around 10.6 million hospital separations (episodes of admitted care) from public and private hospitals in Australia and a quarter of them were from hospitals in Victoria, Australia's second most populous state [40]. The primary aim of this paper is to describe a range of injury outcomes among patients admitted to Victorian hospitals. The outcomes are: complications, 30-day readmissions, LOS, hospital costs, use of CCS, discharge destination and in-hospital death. A secondary aim is to establish the association between each outcome and patient age and sex, body region injured, injury type, injury severity and the presence of comorbidities.

Methods

A retrospective analysis was carried out on existing morbidity data of hospital admitted injury-patients in Victoria; the hospital data was internally linked to enable follow up of cases, in terms of subsequent admissions and in-hospital death. Data provision and linkage was undertaken by the Centre for Victorian Data Linkage (CVDL). Ethics approval was obtained from the Monash University Human Research Ethics Committee.

Data sources

Morbidity data was extracted from the Victorian Admitted Episodes Dataset (VAED), which contains unit records of all public and private hospital admissions in Victoria. Among the information stored in the VAED are patient demographics, morbidity, external causes of morbidity and patient discharge status. Up to forty diagnosis codes can be recorded per patient episode; this includes external cause information. Morbidity information in the VAED is coded according to the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modifications (ICD-10-AM) [41]. Treatment costs at hospitals for each episode were extracted from the Victorian Cost Data Collection (VCDC), these represent the total actual costs of the episodes as reported by the hospital.

Data linkage

VAED hospital admissions data were internally linked within the VAED and linked with VCDC data using variables such as campus code, unique record number and department of health key. Linkage within the VAED was enhanced with the Better Patient Data dataset (which is a separate collection from clinical data, containing identifying information such as patients' names, addresses, sex, date of birth etc.) in order to create across-service patient records. CVDL used deterministic data linkage with some fuzzy matching to allow for slight variation in the linkage variables, such as incorrect names and dates. No clerical review of linkages was carried out but a number of general quality checks were performed by CVDL.

Case selection

Injury cases were selected using a protocol established for previous national reporting in Australia [1]: VAED records with an injury diagnosis (ICD-10-AM diagnosis code in the range "S00" to "T75" or "T79" in the principal diagnosis code). The selected cases were Victorian residents with their index injury hospital admission during the study period. 'Index injury' is the first injury record in the VAED for a patient during that period. Records with an admission source indicating a transfer from another hospital or statistical separation (change in care type within the same hospital) in consecutive records were all considered to be part of the index injury hospitalisation.

Patients with an index injury admission between 01 July 2012 and 30 June 2014 in the VAED were selected. Using internally linked data within the VAED (i.e. using a patient-specific identifier), patients were followed up for all hospital admissions subsequent to their index injury admission. The follow-up times were varied by outcome: one year for in-hospital death and cost, two years for LOS, discharge destination, intensive care unit (ICU) stay and mechanical ventilator (MV) use, and thirty days for readmissions, from the index injury date.

Outcome coding and case exclusions

In-hospital death

In-hospital death was classified as a binary outcome and excluded those whose index stay was longer than 365 days.

Readmissions

Three different forms of readmissions were coded, all with a binary outcome: "1" for patients readmitted within 30 days of index admission discharge and "0" otherwise, limited to the first occurring readmission. The three forms were: 1) at least one *any-cause* readmission; 2) at least one *non-planned* readmission (elective admissions were excluded); and 3) at least one *potentially avoidable* readmission.

Potentially avoidable readmissions in this study were identified using two methods. First, by selecting non-planned readmission records with any primary condition diagnosis code equal to the principal diagnosis code of the index admission. Primary conditions were identified with a prefix "P" in the VAED, which means they existed at the time of hospital admission and were treated or actively monitored during the stay. Second, by using part of the SQLape (Striving for Quality Level and Analyzing of Patient Expenses) algorithm [42]. The algorithm identifies potentially avoidable readmissions as unforeseen readmissions for a previously known affliction. They consist of iatrogenic complications, other healthcare related complications and complications arising from preventable diseases (deep vein thrombosis, pulmonary embolism, decubitus ulcer). In this study, following this algorithm, readmissions with an SQLape listed complication recorded as a primary condition were selected (these complication codes are listed in appendix D of Halfon et al. (2002) [43]). Certain complications from this list were not included in identifying potentially avoidable readmissions as they were irrelevant to the scope of studying injury patients; namely complications related to obstetrics and radiation-induced conditions. Codes related to complications arising from pre-existing diseases were also not considered in identifying potentially avoidable readmissions. The reason being, by including readmissions related to pre-existing conditions, an effect of these conditions becomes inherent in the outcome, whereas the study aims to describe the effect of pre-existing conditions on the outcome. Patients who died in hospital or left against medical advice were excluded from 'readmissions' coding.

Complications

Complications were identified using the Classification of Hospital Acquired Diagnoses (CHADx) [32], a tool developed to code hospital-acquired diagnoses, and commonly used in hospitals in a number of Australian states. The CHADx uses a "condition onset" flag which distinguishes complications from primary diagnoses and comorbidities. The CHADx is grouped into 17 major classes expanding to 144 subclasses and is designed to avoid double counting in sequentially coded diagnosis information. Complications were determined for all index admissions and related readmissions (i.e., readmissions with the same principal diagnosis code as the index principal diagnosis code or a principal readmission diagnosis code of T79, T80-T89 or T90-T98; including complication codes recorded in transfers and statistical separations records). Readmissions that took place later than six months after the index admission were excluded. All complications were computed according to the CHADx hierarchy and summed as a count variable (number of complications).

Costs and LOS

Costs were recorded in Australian dollars (AUD), and LOS (excluding leave with and without permission) in days. The outcomes were cost and LOS of the index admission plus statistical separations and transfers to other hospitals subsequent to the index admission, and readmissions were excluded. Cost data were available for July 2012 to June 2015 allowing only one-year follow-up for patients who entered hospitals after June 2014. For this reason, cost analysis was restricted to patients with a length of stay equal to or less than one year. Cost data was available only for public hospitals and some public

hospital patient records had missing data. Therefore, the cost data analysis was limited to patients admitted to public hospitals with non-missing cost data. This amounted to 77.6% of the index admission cohort; the remaining 22.4% being index injury admissions to private hospitals, patients who stayed more than one year in public hospitals with non-missing data and those with missing cost data for public hospitals. Costs were standardized to 2012 prices using the Australian Consumer Price Index [44].

Discharge destination

Long-term nursing care needs were assessed based on post-hospital discharge destination. Discharge destination was classified into a binary variable with patients either (1a) discharged home with a specific referral for further care to a support service, (1b) transferred to aged care or mental health residential facility or (1c) transferred to other hospital-based care, vs (2) sent home without a referral for further care. Patients who left against medical advice and those who died in hospital were excluded. Further, patients were retained only if the admission source was private residence or accommodation. This step excluded patients transferred from transition care bed-based programs, mental health residential facilities and aged care residential facilities. These patients were excluded as they are most likely to go back to accommodation 'with care' regardless of the injury and demographic factors.

Critical care services

CCS analysed in this study were ICU stay, cardiac care unit (CCU) stay and MV use. CCS were modelled as a binary response.

Factor coding and grouping

Patients were classified into six age groups, closely aligned to the groups used by the Australian Bureau of Statistics [45]; 0–14, 15–24, 25–44, 45–64, 65–84, 85 years and over. Body region groups were created by regrouping the "blocks" contained in the ICD-10-AM Chapter 19 [41] and injury groups according to the injury "type" classification at the three-character level in the same chapter; both based on the principal diagnosis code. Injury severity was calculated using the ICD-based Injury Severity Score (ICISS) [46]. Computation of the ICISS was as follows. First, each injury diagnosis in every record was allocated a survival risk ratio (SRR) (proportion of survivors among all patients with that particular ICD-10-AM diagnosis); SRRs were sourced from the National Injury Surveillance Unit [47]. Next, using the *worst injury* method [48], the lowest SRR was assigned as the ICISS. Finally, a serious injury was considered to be one with an ICISS less than or equal to 0.941 (survival probability of 94.1%) [49]. Socio economic status was classified as per the Socio-Economic Indexes for Areas (SEIFA) [50]. The specific SEIFA used in this study was the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD); with state deciles based on Statistical Local Areas (SLAs). A low score indicates relatively greater disadvantage. Comorbidities were identified using a combination of the Charlson Comorbidity Index (CCI) [51] and Elixhauser Comorbidity Measure (ECM) [52] comorbidity groups. The ICD-10 codes for these conditions were extracted mainly from Quan et al. (2005) [53] and Sundararajan et al. [54]. This included all 17 conditions from the CCI list and all 30 conditions from the ECM list. Thirty-four comorbidity groups were identified in total by combining these two lists, of which three were eventually excluded. The excluded groups were weight loss and fluid-electrolyte disorders, which were more likely to be complications or symptoms, rather than comorbidities, and the group "other neurological disorders" which were a diverse selection of codes that did not narrow down to a specific condition. Additional codes from the Sundararajan list included the following: B23 (HIV/AIDS), C80 (any malignancy), R02 (peripheral vascular disease), N01, N072-N074 (renal disease).

Statistical analysis

Descriptive analysis was undertaken to determine the distribution of outcomes across selected demographic and patient characteristics of the study population; these were captured as frequencies and proportions for binary outcomes, means with 95% confidence intervals (CIs) and medians with inter-quartile ranges (IQRs) for continuous variables.

Sample sizes were large in this study, therefore effect sizes were more meaningful than p values to establish associations between outcomes and population factors [55]. Univariate modelling was carried out using: (i) logistic regression for discharge destination, in-hospital death, CCS use and readmissions, (ii) negative binomial regression for LOS and number of complications and (iii) linear regression with a natural log transformation for costs. The aim of this study was to describe outcomes and their association with factors, therefore establishing associations between outcomes and base factors using univariate analysis was adequate. Additional analysis for associations between outcomes were also carried out using univariate modelling. Once again using simple tests for associations such as the chi squares were not possible with this large dataset, because all results are highly significant and therefore does not provide further insights. Association between the dependent and independent variables were assessed based on effect sizes (using odds ratios (ORs) for logistic regressions, incident

rate ratios (IRRs) for negative binomial regressions and beta coefficients for linear regressions, and their confidence intervals); with an effect size of ±30% considered as notable. The normative (logical) or largest categories were used as reference groups for regression analysis. SAS software, Version 9.4 of the SAS System for Windows [56] and Stata 14.0 (StataCorp) [57] were used to analyse the data.

Results

There were 152,835 patients with an index hospital admission for an injury during the period July 2012 to June 2014. Males represented a higher proportion (55.8%), while patients with serious injury (ICISS less than or equal to 0.941) accounted for 12.5% and those with one or more comorbidities accounted for 19.5%. The body regions most commonly injured were the head (17.0%) and wrist and hand (16.8%) while fractures were the most common type of injury (41.6%) (Table 1).

In-hospital death occurred in 0.9% of the patients during the index admission (includes all statistical separations and transfers within the episode). Patients had on average 2.4 complications (CI 2.4–2.5) with a median of 2 (IQR, 1–3); more than one in four (26.8%) needed care post-discharge from hospital. The mean admission cost of patients was AUD 7013 (CI AUD 6929-AUD 7096); cost data were available only for 77.6% of the 152,835 patients. The median LOS was one day (IQR 1–3). ICU stay was recorded in only 3.0% of patients, while 1.5% used the mechanical ventilator and 0.4% required CCU stay. At least one all-cause readmission occurred in 12.3% of patients, non-planned readmission in 7.9% and a potentially avoidable readmission in 3.2% (Table 2).

Factors associated with in-hospital death

In-hospital death increased with age. Compared to patients in the 65–84-year age group, those who were 85 years and over had over two and a half times the odds of death in hospital while death was far less likely among all other age groups. In-hospital death was not notably different for females and males. Likelihood of death increased with the number of comorbidities; patients with more than three comorbidities had thirty-six times the odds of an in-hospital death than those with no comorbidities. Serious injury compared to non-serious injury had a greater impact on in-hospital death (nearly 17 times the odds). Among patients with serious injury, 5.0% died in hospital. Patients with hip & thigh injuries had around 3.4 times the odds of death in hospital than those with head injuries. Apart from hip & thigh, injury to any other body region had a lesser likelihood of death or was not notably different from the likelihood of death from head injuries. Compared to intracranial injury, most other types of injury had more than 30% lower odds of death. There was no notable difference in the odds of in-hospital death among those in more disadvantaged socio-economic areas against more advantaged areas (Tables 2 and 3).

Factors associated with complications

A total of 49,440 complications were identified in this study population. The top four classes of complications were cardiovascular (13.7%), gastrointestinal (12.3%), metabolic disorders (12.1%) and genitourinary (10. 7%) complications. The most common subclasses were electrolyte disorders without dehydration (6.4%), hypotension (5.8%), alterations to mental state (5.4%), constipation (5.1%) and cardiac arrhythmias, conduction disturbances and abnormal heart beat (4.8%) (Table 4).

The average number, and odds of occurrence of complications increased with increasing age and with increasing number of comorbidities. The odds of complications were higher for patients with serious injury. The likelihood of complications varied by body region, with injuries to neck, thorax, shoulder and upper arm and some lower extremities incurring higher likelihood of complications than head injuries. Complications were more likely to occur in those with injury to internal organs (64% higher odds) compared to those with fractures (Tables 2 and 3). There was no notable difference in likelihood of complications between socio-economic areas.

Factors associated with discharge destination

More than one-fifth of patients required further support services after discharge from hospital. This was observed in all age groups, with higher odds in children and those 85 years and over compared to the reference group (65–84 years). The impact of gender did not stand out (females 8% higher odds than males) while more severe injuries and increasing number of comorbidities increased the odds of needing support services. Patients with upper limb and hip and thigh injuries were more likely to require further care compared to head injuries. Patients with eye injuries were more likely to require further care compared to fractures. The likelihood of being discharged to care with support services decreased with increase in socioeconomic advantage (Tables 2 and 3).

Factors associated with cost

The cost of treating patients increased with increasing patient age, number of comorbidities, injury severity and female gender. Severe injuries and increasing number of comorbidities increased the likelihood of higher costs. The highest likelihood of increased costs were for knee and lower leg and hip and thigh injuries compared to head injuries, while injuries to most other body parts were also likely to increase costs compared to head

Table 1 Overview of study population: hospital-admitted injury patients, Victoria

	Injury hospital admisions[a]	
	July 2012 to June 2014	
Total number of patients	152,835	
Age group (years)		
0–14 years	21,058	13.8
15–24 years	22,851	15.0
25–44 years	35,394	23.2
45–64 years	29,325	19.2
65–84 years	27,886	18.3
85 and over	16,321	10.7
Gender		
Male[b]	85,329	55.8
Female	67,506	44.2
Injury severity[c]		
Serious injury (ICISS< 0.941)	19,095	12.5
Other injury (ICISS> = 0.941)	133,740	87.5
Number of comorbidities		
0	123,046	80.5
1	21,046	13.8
2	5699	3.7
3	2120	1.4
> 3	924	0.6
Body region		
Head	25,982	17.0
Neck	3428	2.2
Thorax	7359	4.8
Abdomen, lower back, lumbar spine & pelvis	9410	6.2
Shoulder & upper arm	11,224	7.3
Elbow & forearm	15,465	10.1
Wrist & hand	25,722	16.8
Hip & thigh	12,862	8.4
Knee & lower leg	19,806	13.0
Ankle & foot	5662	3.7
Foreign body (various regions)	2585	1.7
Burns (various regions)	1802	1.2
Multiple body regions	36	0.0
Unspecified body region	534	0.4
Body region not relevant	10,958	7.2
Grouped injury type (first occurring)		
Superficial injury	7364	4.8
Open wound	21,309	13.9
Fracture	63,505	41.6
Dislocation, sprain & strain	10,502	6.9
Injury to nerves & spinal cord	1990	1.3
Injury to blood vessels	1332	0.9

Table 1 Overview of study population: hospital-admitted injury patients, Victoria *(Continued)*

	Injury hospital admisions[a]	
	July 2012 to June 2014	
Total number of patients	152,835	
Injury to muscle & tendon	8205	5.4
Crushing injury	326	0.2
Traumatic amputation	1588	1.0
Eye injury- excluding foreign body	481	0.3
Intracranial injury	6038	4.0
Injury to internal organs	1684	1.1
Foreign body	2585	1.7
Burns	1802	1.2
Other and unspecified injury	13,166	8.6
Systemic-poisoning/toxic effects	9782	6.4
Other effects of external cause/complication	1176	0.8
Socio-Economic Indexes for Areas (SEIFA)[d]		
1	16,548	10.8
2	#	#
3	9982	6.5
4	16,954	11.1
5	10,147	6.6
6	11,217	7.3
7	11,123	7.3
8	24,412	16.0
9	22,627	14.8
10	21,648	14.2
999 (missing)	< 5	< 5

Notes:
[a]Total number of patients with an index admission to all public and private hospitals in Victoria, limited to Victorian residents with an ICD-10-AM diagnosis code in the range "S00" to "T75" or "T79" in the principal diagnosis
[b]Intersex patient count less than 3 added to the majority sex group to protect confidentiality
[c]Worst injury method-ICD-based Injury Severity Score less than or equal to 0.941 considered as serious injury
[d]SEIFA used in this study is the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD), are state deciles based on Statistical Local Areas (SLAs). A low score indicates relatively greater disadvantage. For further information
refer http://www.abs.gov.au/ausstats/abs@.nsf/lookup/2033.0.55.001main+features100042011
< 5 Cells with frequency less than 5 or statistics based on less than 5 patients has been suppressed for confidentiality reasons. # Other cells may also be suppressed to protect the confidentiality of < 5 cells

injuries. Compared to fractures, injuries to internal organs were more likely to increase costs while all other injury types were likely to result in lower costs or did not produce a notable difference. There was no notable difference in likelihood of incurring higher costs between socioeconomic areas (Tables 2 and 3).

Factors associated with LOS

The median LOS (in days) was greater for those aged 65–84 (3, IQR 1–13) and 85 years and over (6, IQR 1–21) as opposed to the younger age groups (1, IQR 1–3). Relative to the 65–84 years age group, those 85 years and above were 36% more likely to have a longer LOS and those in the younger age groups were around 60–87% less likely. The mean LOS was 5.4 days (not shown in tables). Although the gender difference in median LOS was not notable, the mean was 4.1 days for males and 7.1 days for females (not shown in tables). Severe injuries and more comorbidities were associated with greater LOS. Injuries to the neck, trunk, shoulder and upper arm and lower extremities compared to the head had higher incident rates. Fractures had higher incident rates compared to most other types of injuries. There was no notable difference in incident rates between socioeconomic areas (Tables 2 and 3).

Factors associated with CCS use

ICU stay and MV use proportions and the likelihood of using these services was highest among those aged 25–

Table 2 Description of injury outcomes by population groups

	Outcomes				
	In-hospital death, n (%)[a]	Average number of CHADx complications[b], mean (CI)	Care needed post index admission discharge[c], n (%)	Hospital cost of index admission[d,a] (A$), mean (CI)	Length of stay of index admission (days), median (IQR)
No of patients selected for analysis	152,795	152,835	148,539	118,570	152,835
No of patients with outcome	1341	20300[e]	39,731	118,570	152,835
Overall indicator	0.9%	2.4 (2.4–2.5)	26.8%	7013 (6929–7096)	1 (1–3)
Age group (years)					
0–14 years	9 (0.0)	1.5 (1.4–1.6)	7451 (35.5)	3221 (3092–3350)	1 (1–1)
15–24 years	13 (0.1)	1.8 (1.7–1.9)	5282 (23.5)	4639 (4476–4802)	1 (1–1)
25–44 years	57 (0.2)	1.9 (1.8–1.9)	7606 (21.9)	5311 (5156–5466)	1 (1–2)
45–64 years	79 (0.3)	2.1 (2.0–2.1)	6318 (21.9)	6864 (6658–7071)	1 (1–3)
65–84 years	459 (1.6)	2.6 (2.6–2.7)	7261 (27.0)	11,484 (11233–11,736)	3 (1–13)
85 and over	724 (4.4)	2.9 (2.9–3.0)	5813 (39.8)	13,380 (13067–13,694)	6 (1–21)
Gender					
Male	671 (0.8)	2.4 (2.3–2.4)	21,698 (26.1)	6336 (6225–6446)	1 (1–2)
Female	670 (1.0)	2.5 (2.4–2.5)	18,033 (27.6)	7889 (7762–8017)	1 (1–5)
Number of comorbidities[f]					
0	430 (0.3)	2.1 (2.1–2.2)	30,797 (25.5)	5373 (5298–5448)	1 (1–2)
1	379 (1.8)	2.7 (2.6–2.7)	5891 (29.6)	10,725 (10447–11,003)	2 (1–10)
2	276 (4.8)	3.0 (2.9–3.1)	1942 (37.6)	17,230 (16497–17,964)	6 (2–20)
3	152 (7.2)	3.2 (3.0–3.3)	745 (39.4)	21,173 (20059–22,288)	10 (4–27)
> 3	104 (11.3)	3.6 (3.4–3.9)	356 (45.6)	29,884 (27596–32,172)	18 (7–36)
Injury severity[g]					
Serious injury (ICISS< 0.941)	945 (5.0)	3.1 (3.0–3.1)	6617 (38.0)	21,019 (20544–21,494)	9 (3–26)
Other injury (ICISS> = 0.941)	396 (0.3)	1.9 (1.9–2.0)	33,114 (25.3)	4988 (4931–5045)	1 (1–2)
Body region					
Head	312 (1.2)	2.5 (2.4–2.6)	5533 (22.1)	4974 (4774–5173)	1 (1–1)
Neck	42 (1.2)	2.6 (2.4–2.9)	630 (19.0)	7879 (6966–8791)	1 (1–3)
Thorax	99 (1.3)	2.5 (2.4–2.6)	1382 (19.4)	8614 (8132–9095)	2 (1–7)
Abdomen, lower back, lumbar spine & pelvis	106 (1.1)	2.4 (2.3–2.5)	2319 (25.6)	8894 (8488–9300)	2 (1–11)
Shoulder & upper arm	74 (0.7)	2.0 (1.9–2.1)	2825 (25.7)	7192 (6938–7445)	1 (1–3)
Elbow & forearm	21 (0.1)	1.7 (1.6–1.7)	4456 (29.2)	5257 (5132–5382)	1 (1–2)
Wrist & hand	7 (0.0)	1.4 (1.3–1.5)	7980 (31.3)	3259 (3206–3312)	1 (1–1)
Hip & thigh	503 (3.9)	3.1 (3.0–3.2)	4623 (39.0)	18,695 (18306–19,084)	8 (2–26)
Knee & lower leg	52 (0.3)	1.9 (1.9–2.0)	4903 (25.1)	9273 (9011–9536)	2 (1–4)
Ankle & foot	7 (0.1)	1.8 (1.6–1.9)	1338 (24.0)	5158 (4881–5436)	1 (1–2)
Foreign body	11 (0.4)	1.8 (1.6–2.1)	617 (24.4)	2879 (2697–3060)	1 (1–2)
Burns	6 (0.3)	2.6 (2.3–2.8)	608 (34.3)	10,265 (8864–11,666)	1 (1–4)
Multiple body regions	0 (0.0)	2.0 (0.9–3.1)	7 (21.2)	3888 (1728–6049)	1 (1–2)
Unspecified body region	2 (0.4)	1.9 (1.4–2.3)	84 (16.2)	4869 (3663–6076)	1 (1–4)
Body region not relevant	99 (0.9)	2.2 (2.1–2.4)	2426 (23.2)	5417 (5148–5687)	1 (1–3)

Table 2 Description of injury outcomes by population groups *(Continued)*

Grouped injury type (first occurring)						
Superficial injury	32 (0.4)	1.9 (1.8–2.1)	1363 (19.1)	3547 (3371–3723)		1 (1–2)
Open wound	44 (0.2)	1.7 (1.7–1.8)	6065 (29.2)	3352 (3266–3438)		1 (1–4)
Fracture	769 (1.2)	2.6 (2.6–2.6)	19,884 (32.2)	10,096 (9959–10,232)		2 (1–6)
Dislocation, sprain & strain	18 (0.2)	1.6 (1.5–1.8)	1515 (14.5)	4005 (3820–4191)		1 (1–1)
Injury to nerves & spinal cord	11 (0.6)	2.7 (2.3–3.2)	612 (31.2)	11,097 (9125–13,069)		1 (1–2)
Injury to blood vessels	7 (0.5)	1.9 (1.6–2.3)	389 (29.8)	8686 (7363–10,009)		1 (1–2)
Injury to muscle & tendon	5 (0.1)	1.6 (1.5–1.7)	1806 (22.2)	4075 (3923–4227)		1 (1–2)
Crushing injury	0 (0.0)	1.2 (0.8–1.5)	86 (26.5)	2428 (1841–3015)		1 (1–1)
Traumatic amputation	< 5	2.0 (1.7–2.4)	550 (34.8)	5758 (5151–6366)		1 (1–2)
Eye injury- excluding foreign body	< 5	1.9 (1.4–2.3)	227 (48.4)	5862 (4676–7048)		1 (1–3)
Intracranial injury	260 (4.3)	3.0 (2.9–3.2)	1066 (19.0)	9675 (8970–10,380)		1 (1–5)
Injury to internal organs	27 (1.6)	2.7 (2.5–2.9)	431 (26.8)	14,381 (13146–15,616)		4 (2–8)
Foreign body	11 (0.4)	1.8 (1.6–2.1)	617 (24.4)	2879 (2697–3060)		1 (1–1)
Burns	6 (0.3)	2.6 (2.3–2.8)	608 (34.3)	10,265 (8864–11,666)		1 (1–5)
Other and unspecified injury	50 (0.4)	1.8 (1.7–1.9)	2086 (16.4)	3189 (3062–3317)		1 (1–1)
Systemic-poisoning/toxic effects	52 (0.5)	2.1 (2.0–2.3)	2175 (23.2)	4794 (4566–5022)		1 (1–2)
Other effects of external cause/ complication	47 (4.0)	2.6 (2.3–3.0)	251 (22.9)	11,259 (9494–13,023)		2 (1–6)
SEIFA						
1	152 (0.9)	2.5 (2.4–2.6)	5142 (32.1)	6990 (6767–7214)		1 (1–3)
2	#	2.4 (2.3–2.6)	#	#		1 (1–3)
3	112 (1.1)	2.5 (2.4–2.6)	2745 (28.4)	7391 (7087–7695)		1 (1–4)
4	154 (0.9)	2.4 (2.3–2.5)	5274 (32.2)	7341 (7081–7602)		1 (1–3)
5	87 (0.9)	2.4 (2.3–2.5)	3057 (30.8)	6412 (6135–6688)		1 (1–2)
6	85 (0.8)	2.3 (2.2–2.4)	3057 (27.9)	6824 (6494–7153)		1 (1–3)
7	75 (0.7)	2.5 (2.4–2.6)	2987 (27.5)	7079 (6780–7377)		1 (1–3)
8	207 (0.8)	2.4 (2.4–2.5)	5156 (21.7)	6736 (6526–6947)		1 (1–3)
9	197 (0.9)	2.4 (2.4–2.5)	5632 (25.6)	7069 (6841–7297)		1 (1–3)
10	195 (0.9)	2.4 (2.4–2.5)	4000 (19.0)	7066 (6816–7315)		1 (1–3)
999	< 5	–	< 5	< 5		< 5
	Outcomes					
	Use of critical care services at index admission n (%)			Readmission[h], n (%)		
	ICU stay > 0 h	MV use > 0 h	CCU stay > 0 h	30 day-all-cause	30 day -non-planned	30 day-potentially avoidable
No of patients selected for analysis	152,835	152,835	152,835	149,943	149,943	149,943
No of patients with outcome	4519	2234	664	18,514	11,803	4777
Overall indicator	3.0%	1.5%	0.4%	12.3%	7.9%	3.2%
Age group (years)						
0–14 years	158 (0.8)	77 (0.4)	8 (0.0)	1346 (6.4)	856 (4.1)	380 (1.8)
15–24 years	687 (3.0)	418 (1.8)	64 (0.3)	1893 (8.4)	1244 (5.5)	512 (2.3)
25–44 years	1244 (3.5)	780 (2.2)	94 (0.3)	3508 (10.1)	2369 (6.8)	1083 (3.1)
45–64 years	1069 (3.6)	563 (1.9)	143 (0.5)	3627 (12.5)	2182 (7.5)	1000 (3.5)
65–84 years	962 (3.4)	332 (1.2)	222 (0.8)	4992 (18.3)	3032 (11.1)	1123 (4.1)
85 and over	399 (2.4)	64 (0.4)	133 (0.8)	3148 (20.3)	2120 (13.6)	679 (4.4)

Table 2 Description of injury outcomes by population groups *(Continued)*

Gender						
Male	2645 (3.1)	1429 (1.7)	325 (0.4)	9292 (11.1)	6071 (7.3)	2647 (3.2)
Female	1874 (2.8)	805 (1.2)	339 (0.5)	9222 (13.9)	5732 (8.6)	2130 (3.2)
Number of comorbidities[f]						
0	1936 (1.6)	924 (0.8)	310 (0.3)	13,105 (10.8)	8091 (6.7)	3490 (2.9)
1	1400 (6.7)	746 (3.5)	175 (0.8)	3491 (17.2)	2339 (11.5)	818 (4.0)
2	724 (12.7)	366 (6.4)	106 (1.9)	1172 (22.1)	825 (15.6)	277 (5.2)
3	280 (13.2)	135 (6.4)	42 (2.0)	484 (25.1)	346 (17.9)	124 (6.4)
> 3	179 (19.4)	63 (6.8)	31 (3.4)	262 (32.3)	202 (24.9)	68 (8.4)
Injury severity[g]						
Serious injury (ICISS< 0.941)	2367 (12.4)	1171 (6.1)	192 (1.0)	3364 (18.8)	2366 (13.2)	953 (5.3)
Other injury (ICISS> = 0.941)	2152 (1.6)	1063 (0.8)	472 (0.4)	15,150 (11.5)	9437 (7.1)	3824 (2.9)
Body region						
Head	783 (3.0)	604 (2.3)	87 (0.3)	2654 (10.4)	1894 (7.5)	629 (2.5)
Neck	147 (4.3)	77 (2.2)	13 (0.4)	351 (10.5)	261 (7.8)	93 (2.8)
Thorax	617 (8.4)	224 (3.0)	59 (0.8)	1046 (14.6)	739 (10.3)	227 (3.2)
Abdomen, lower back, lumbar spine & pelvis	346 (3.7)	125 (1.3)	31 (0.3)	1501 (16.3)	1031 (11.2)	354 (3.9)
Shoulder & upper arm	100 (0.9)	27 (0.2)	38 (0.3)	1602 (14.4)	955 (8.6)	432 (3.9)
Elbow & forearm	48 (0.3)	15 (0.1)	47 (0.3)	1925 (12.5)	1069 (7.0)	519 (3.4)
Wrist & hand	27 (0.1)	10 (0.0)	57 (0.2)	2046 (8.0)	1149 (4.5)	572 (2.2)
Hip & thigh	557 (4.3)	81 (0.6)	109 (0.8)	2249 (18.3)	1475 (12.0)	532 (4.3)
Knee & lower leg	147 (0.7)	37 (0.2)	59 (0.3)	2260 (11.5)	1298 (6.6)	703 (3.6)
Ankle & foot	15 (0.3)	6 (0.1)	8 (0.1)	653 (11.7)	441 (7.9)	241 (4.3)
Foreign body	43 (1.7)	21 (0.8)	11 (0.4)	228 (9.0)	143 (5.6)	37 (1.5)
Burns	113 (6.3)	75 (4.2)	7 (0.4)	275 (15.5)	222 (12.5)	138 (7.8)
Multiple body regions	< 5	0 (0.0)	0 (0.0)	7 (21.2)	< 5	0 (0.0)
Unspecified body region	< 5	0 (0.0)	0 (0.0)	81 (15.4)	#	12 (2.3)
Body region not relevant	1573 (14.4)	932 (8.5)	138 (1.3)	1636 (15.6)	1075 (10.2)	288 (2.7)
Grouped injury type (first occurring)						
Superficial injury	56 (0.8)	26 (0.4)	15 9 (0.2)	853 (11.7)	565 (7.8)	157 (2.2)
Open wound	86 (0.4)	43 (0.2)	60 (0.3)	1984 (9.4)	1226 (5.8)	523 (2.5)
Fracture	1431 (2.3)	390 (0.6)	314 (0.5)	8868 (14.2)	5431 (8.7)	2642 (4.2)
Dislocation, sprain & strain	28 (0.3)	< 5	13 (0.1)	902 (8.6)	556 (5.3)	216 (2.1)
Injury to nerves & spinal cord	53 (2.7)	34 (1.7)	5 (0.3)	176 (9.0)	116 (5.9)	47 (2.4)
Injury to blood vessels	49 (3.7)	30 (2.3)	7 (0.5)	107 (8.2)	66 (5.0)	#
Injury to muscle & tendon	#	< 5	13 (0.2)	634 (7.8)	368 (4.5)	162 (2.0)
Crushing injury	0 (0.0)	0 (0.0)	0 (0.0)	27 (8.3)	14 (4.3)	< 5
Traumatic amputation	11 (0.7)	9 (0.6)	< 5	187 (11.8)	103 (6.5)	66 (4.2)
Eye injury- excluding foreign body	< 5	< 5	< 5	92 (19.4)	63 (13.3)	23 (4.8)
Intracranial injury	587 (9.7)	466 (7.7)	38 (0.6)	689 (12.2)	526 (9.3)	181 (3.2)
Injury to internal organs	426 (25.3)	180 (10.7)	18 (1.1)	233 (14.4)	197 (12.2)	72 (4.5)
Foreign body	43 (1.7)	21 (0.8)	11 (0.4)	228 (9.0)	143 (5.6)	37 (1.5)

Table 2 Description of injury outcomes by population groups *(Continued)*

Burns	113 (6.3)	75 (4.2)	7 (0.4)	275 (15.5)	222 (12.5)	138 (7.8)
Other and unspecified injury	43 (0.3)	20 (0.2)	22 (0.2)	1623 (12.5)	1132 (8.7)	198 (1.5)
Systemic-poisoning/toxic effects	1451 (14.8)	853 (8.7)	126 (1.3)	1483 (15.8)	973 (10.4)	247 (2.6)
Other effects of external cause/ complication	122 (10.4)	79 (6.7)	12 (1.0)	153 (13.9)	102 (9.2)	41 (3.7)
SEIFA	614 (3.7)	277 (1.7)	52 (0.3)	1906 (11.8)	1335 (8.3)	554 (3.4)
1	#	#	#	#	#	#
2	395 (4.0)	155 (1.6)	69 (0.7)	1212 (12.4)	816 (8.4)	348 (3.6)
3	539 (3.2)	275 (1.6)	67 (0.4)	2095 (12.6)	1404 (8.5)	538 (3.2)
4	281 (2.8)	150 (1.5)	30 (0.3)	1086 (10.9)	716 (7.2)	302 (3.0)
5	323 (2.9)	184 (1.6)	41 (0.4)	1340 (12.2)	904 (8.2)	394 (3.6)
6	309 (2.8)	152 (1.4)	42 (0.4)	1265 (11.6)	857 (7.8)	350 (3.2)
7	666 (2.7)	359 (1.5)	130 (0.5)	2924 (12.2)	1862 (7.8)	775 (3.2)
8	581 (2.6)	284 (1.3)	115 (0.5)	2849 (12.8)	1711 (7.7)	652 (2.9)
9	526 (2.4)	281 (1.3)	108 (0.5)	2792 (13.1)	1520 (7.1)	598 (2.8)
10	< 5	< 5	< 5	< 5	< 5	< 5
999	614 (3.7)	277 (1.7)	52 (0.3)	1906 (11.8)	1335 (8.3)	554 (3.4)

Note:
[a]Patients whose LOS was > 365 days were excluded
[b]Complications listed in the index admission and related readmissions, includes statistical separations and transfers
[c]Includes separation to private residence/accommodation with support services, inpatient rehabilitation or institutional care, excludes patients who left against medical advice or died in hospital and those who did not originally come from private residence/accommodation
[d]Patients with cost data available in public hospitals only, includes statistical separations and transfers to other hospitals, standardised 2012 prices
[e]Presence of at least one CHADx code
[f]Comorbidities identified using Charlson and Elixhauser algorithms
[g]Worst injury method-ICD-based Injury Severity Score less than or equal to 0.941 considered as serious injury
[h]Eligible index admissions excluded patients who died in hospital or left against medical advice
< 5 Cells with frequency less than 5 or statistics based on less than 5 patients has been suppressed for confidentiality reasons. # Other cells may also be suppressed to protect the confidentiality of < 5 cells

44 years and 45–64-year age group, while CCU use was greater among the 65–84-year and 86 years and over age groups. Females were more likely to stay in the CCU but gender was not statistically significantly with ICU and MV use. Severe injuries and comorbidities were associated with increased likelihood of CCS use. The body region injured and the type of injury affected the likely use of CCSs. The likelihood of ICU-stay and MV use were less as the socioeconomic advantage increased while it was the opposite for CCU stay (Tables 2 and 3).

Factors associated with readmission

The proportions of cases with 30-day readmissions increased with increasing age, injury severity and number of comorbidities. Potentially-avoidable readmissions within 30 days were equally common among males and females than the other two types of readmissions, which were more common among females. The likelihood of readmission was notably lower in the 0–14 and 15–24-year-old age groups compared to the 65–84-year (reference) age group for all three types of readmissions, while the 25–44- and 45–64-year age groups also had a notably lower likelihood of all-cause and non-planned readmissions compared to the 65–84-year (reference) age group. The effect of gender was not notable among all three types of readmissions while severe injuries were more than 70% more likely to result in any type of readmission. Increasing number of comorbidities increased the likelihood of all three types of readmissions. Injuries to the trunk and hip and thigh and burns to some body regions were more likely to result in any type of readmissions compared to the head, while shoulder and upper arm injuries were more likely to result in all-cause and potentially avoidable readmissions. Knee and lower leg and ankle and foot injuries were also more likely to result in potentially avoidable readmissions. Compared to fractures, eye injuries were more likely to result in all-cause readmissions and non-planned readmissions, while injury to internal organs were more likely to result in non-planned readmissions. Burns were more likely to result in both non-planned and potentially avoidable readmissions compared to fractures. There was no notable difference in likelihood of 30-day readmissions between socioeconomic areas (Tables 2 and 3).

Associations between outcomes

Many of the outcomes were associated with each other. The results and a discussion of this analysis is provided

Table 3 Associations between injury outcomes and population groups: results of univariate modelling

	Outcomes				
	In-hospital death OR (95% CI)	Number of complications IRR (95% CI)	Care needed post index admission discharge OR (95% CI)	Hospital cost (index admission) Beta coefficient (95% CI)	Length of stay (days) IRR (95% CI)
Age group (years)					
0–14 years	0.03 (0.01–0.05)	0.07 (0.06–0.08)	1.48 (1.43–1.54)	− 0.86 (− 0.89–0.84)	0.13 (0.13–0.13)
15–24 years	0.03 (0.02–0.06)	0.17 (0.16–0.18)	0.83 (0.79–0.86)	− 0.61 (− 0.64–0.59)	0.21 (0.20–0.21)
25–44 years	0.10 (0.07–0.13)	0.21 (0.20–0.22)	0.76 (0.73–0.79)	− 0.53 (− 0.55–0.51)	0.26 (0.26–0.27)
45–64 years	0.16 (0.13–0.20)	0.35 (0.33–0.36)	0.76 (0.73–0.78)	− 0.37 (− 0.39–0.34)	0.40 (0.40–0.41)
65–84 years	Reference	Reference	Reference	Reference	Reference
85 and over	2.78 (2.46–3.12)	1.53 (1.45–1.62)	1.78 (1.71–1.86)	0.17 (0.14–0.19)	1.36 (1.33–1.39)
Gender					
Male	Reference	Reference	Reference	Reference	Reference
Female	1.26 (1.14–1.41)	1.79 (1.73–1.86)	1.08 (1.06–1.11)	0.09 (0.07–0.10)	1.73 (1.71–1.75)
Number of comorbidities					
0	Reference	Reference	Reference	Reference	Reference
1	5.23 (4.55–6.01)	3.26 (3.11–3.41)	1.23 (1.19–1.27)	0.53 (0.51–0.55)	2.59 (2.54–2.64)
2	14.53 (12.46–16.94)	5.80 (5.36–6.27)	1.76 (1.66–1.86)	1.14 (1.10–1.17)	3.99 (3.86–4.12)
3	22.08 (18.25–26.70)	7.76 (6.85–8.79)	1.90 (1.73–2.09)	1.47 (1.41–1.52)	5.00 (4.75–5.27)
> 3	36.16 (28.88–45.28)	10.92 (9.07–13.16)	2.45 (2.13–2.83)	1.94 (1.86–2.02)	6.93 (6.41–7.49)
Injury severity					
Serious injury (ICISS< 0.941)	17.56 (15.60–19.76)	8.83 (8.48–9.19)	1.81 (1.75–1.87)	1.46 (1.44–1.48)	5.08 (4.99–5.17)
Other injury (ICISS> = 0.941)	Reference	Reference	Reference	Reference	Reference
Body region					
Head	Reference	Reference	Reference	Reference	Reference
Neck	1.02 (0.74–1.41)	1.76 (1.58–1.96)	0.82 (0.75–0.90)	0.28 (0.24–0.32)	1.75 (1.67–1.82)
Thorax	1.12 (0.89–1.41)	2.65 (2.45–2.86)	0.85 (0.79–0.91)	0.59 (0.56–0.63)	1.96 (1.90–2.02)
Abdomen, lower back, lumbar spine & pelvis	0.94 (0.75–1.17)	2.71 (2.53–2.91)	1.21 (1.15–1.28)	0.60 (0.57–0.63)	2.52 (2.45–2.59)
Shoulder & upper arm	0.55 (0.42–0.70)	1.38 (1.28–1.48)	1.22 (1.16–1.28)	0.59 (0.56–0.62)	1.42 (1.38–1.46)
Elbow & forearm	0.11 (0.07–0.17)	0.64 (0.59–0.68)	1.45 (1.38–1.52)	0.53 (0.50–0.55)	0.76 (0.74–0.78)
Wrist & hand	0.02 (0.01–0.05)	0.18 (0.16–0.19)	1.60 (1.54–1.67)	0.23 (0.20–0.25)	0.40 (0.39–0.41)
Hip & thigh	3.35 (2.90–3.86)	7.10 (6.68–7.54)	2.25 (2.15–2.36)	1.60 (1.57–1.62)	4.47 (4.36–4.59)
Knee & lower leg	0.22 (0.16–0.29)	1.34 (1.26–1.42)	1.18 (1.13–1.23)	0.92 (0.89–0.94)	1.67 (1.63–1.70)

Table 3 Associations between injury outcomes and population groups: results of univariate modelling *(Continued)*

Ankle & foot	0.10 (0.05–0.22)	0.64 (0.58–0.71)	1.11 (1.04–1.19)	0.34 (0.30–0.37)	0.94 (0.91–0.98)
Foreign body	0.35 (0.19–0.64)	0.45 (0.38–0.53)	1.14 (1.03–1.25)	− 0.04 (− 0.09–0.01)	0.40 (0.38–0.43)
Burns	0.28 (0.12–0.62)	1.94 (1.68–2.23)	1.84 (1.66–2.04)	0.43 (0.38–0.49)	1.71 (1.62–1.81)
Multiple body regions	##	1.11 (0.38–3.23)	0.95 (0.41–2.18)	0.07 (−0.37–0.51)	1.63 (1.10–2.41)
Unspecified body region	0.31 (0.08–1.24)	0.85 (0.63–1.14)	0.68 (0.54–0.86)	0.07 (− 0.05–0.19)	1.26 (1.14–1.40)
Body region not relevant	0.75 (0.60–0.94)	1.18 (1.10–1.27)	1.06 (1.01–1.12)	0.10 (0.07–0.12)	1.01 (0.98–1.03)
Grouped injury type (first occurring)					
Superficial injury	0.10 (0.07–0.14)	0.29 (0.26–0.32)	0.50 (0.47–0.53)	−1.03 (−1.06–-1.00)	0.44 (0.43–0.46)
Open wound	0.05 (0.03–0.06)	0.17 (0.16–0.18)	0.87 (0.84–0.90)	− 0.88 (− 0.90–-0.86)	0.31 (0.30–0.32)
Fracture	0.27 (0.24–0.31)	Reference	Reference	Reference	Reference
Dislocation, sprain & strain	0.04 (0.02–0.06)	0.20 (0.18–0.22)	0.36 (0.34–0.38)	−0.87 (− 0.90–-0.84)	0.27 (0.26–0.28)
Injury to nerves & spinal cord	0.12 (0.07–0.23)	0.42 (0.36–0.49)	0.95 (0.87–1.05)	−0.22 (− 0.27–-0.16)	0.72 (0.68–0.76)
Injury to blood vessels	0.12 (0.06–0.25)	0.30 (0.25–0.37)	0.89 (0.79–1.00)	−0.03 (− 0.10–0.04)	0.43 (0.40–0.46)
Injury to muscle & tendon	0.01 (0.01–0.03)	0.16 (0.14–0.17)	0.60 (0.57–0.63)	−0.57 (− 0.61–-0.54)	0.26 (0.26–0.27)
Crushing injury	##	0.04 (0.02–0.09)	0.76 (0.59–0.97)	− 1.13 (− 1.28–-0.98)	0.18 (0.15–0.21)
Traumatic amputation	0.01 (0.00–0.10)	0.24 (0.20–0.30)	1.12 (1.01–1.25)	− 0.36 (− 0.42–-0.29)	0.31 (0.29–0.33)
Eye injury- excluding foreign body	0.05 (0.01–0.33)	0.31 (0.22–0.43)	1.97 (1.64–2.37)	− 0.54 (− 0.64–-0.43)	0.39 (0.35–0.44)
Intracranial injury	Reference	1.05 (0.96–1.13)	0.49 (0.46–0.53)	−0.59 (− 0.62–-0.56)	1.03 (1.00–1.07)
Injury to internal organs	0.36 (0.24–0.54)	1.64 (1.42–1.89)	0.77 (0.69–0.86)	0.40 (0.34–0.46)	1.04 (0.98–1.10)
Foreign body	0.09 (0.05–0.17)	0.17 (0.14–0.20)	0.68 (0.62–0.75)	− 0.99 (− 1.03–-0.94)	0.19 (0.18–0.20)
Burns	0.07 (0.03–0.17)	0.73 (0.63–0.85)	1.10 (0.99–1.21)	− 0.51 (− 0.57–-0.46)	0.79 (0.75–0.84)
Other and unspecified injury	0.08 (0.06–0.11)	0.23 (0.22–0.25)	0.41 (0.39–0.43)	− 1.20 (− 1.22–-1.18)	0.42 (0.41–0.43)
Systemic-poisoning/toxic effects	0.12 (0.09–0.16)	0.39 (0.36–0.42)	0.64 (0.61–0.67)	−0.91 (− 0.93–-0.88)	0.40 (0.39–0.41)
Other effects of external cause/ complication	0.92 (0.67–1.27)	0.91 (0.76–1.09)	0.62 (0.54–0.72)	−0.34 (− 0.41–-0.27)	1.03 (0.96–1.10)
SEIFA					
1	Reference	Reference	Reference	Reference	Reference
2	1.03 (0.78–1.35)	1.04 (0.95–1.15)	1.08 (1.02–1.14)	0.16 (0.12–0.19)	1.00 (0.96–1.03)
3	1.22 (0.96–1.56)	1.14 (1.04–1.24)	0.84 (0.79–0.89)	0.10 (0.07–0.14)	1.05 (1.02–1.09)
4	0.99 (0.79–1.24)	0.90 (0.83–0.97)	1.00 (0.96–1.05)	−0.04 (−0.07–-0.02)	1.04 (1.01–1.07)
5	0.93 (0.72–1.22)	0.83 (0.76–0.91)	0.94 (0.89–0.99)	0.02 (−0.01–0.05)	0.88 (0.85–0.91)
6	0.82 (0.63–1.08)	0.82 (0.75–0.89)	0.82 (0.77–0.86)	−0.03 (− 0.06–0.00)	0.89 (0.86–0.92)
7	0.73 (0.55–0.97)	1.01 (0.92–1.10)	0.80 (0.76–0.84)	− 0.05 (− 0.08–-0.02)	1.01 (0.98–1.04)
8	0.92 (0.75–1.14)	0.96 (0.89–1.03)	0.58 (0.56–0.61)	−0.07 (− 0.10–-0.04)	0.96 (0.93–0.98)
9	0.95 (0.77–1.17)	1.00 (0.93–1.07)	0.73 (0.70–0.76)	− 0.10 (− 0.13–-0.08)	1.04 (1.01–1.07)
10	0.98 (0.79–1.21)	1.02 (0.95–1.10)	0.50 (0.47–0.52)	−0.09 (− 0.12–-0.06)	1.04 (1.02–1.07)
999	##	##	##	0.03 (−2.33–2.40)	0.18 (0.02–1.74)

Table 3 Associations between injury outcomes and population groups: results of univariate modelling *(Continued)*

	Outcomes					
	ICU stay OR (95% CI)	MV use OR (95% CI)	CCU stay OR (95% CI)	30 day-all-cause readmission OR (95% CI)	30 day-non-planned readmission OR (95% CI)	30 day-potentially avoidable readmission OR (95% CI)
Age group (years)						
0–14 years	0.21 (0.18–0.25)	0.30 (0.24–0.39)	0.05 (0.02–0.10)	0.31 (0.29–0.32)	0.34 (0.31–0.37)	0.43 (0.38–0.48)
15–24 years	0.87 (0.79–0.96)	1.55 (1.34–1.79)	0.35 (0.26–0.46)	0.41 (0.39–0.43)	0.47 (0.44–0.50)	0.54 (0.49–0.60)
25–44 years	1.02 (0.94–1.11)	1.87 (1.64–2.13)	0.33 (0.26–0.42)	0.50 (0.48–0.52)	0.58 (0.55–0.62)	0.75 (0.69–0.82)
45–64 years	1.06 (0.97–1.16)	1.62 (1.42–1.86)	0.61 (0.49–0.75)	0.64 (0.61–0.67)	0.65 (0.62–0.69)	0.83 (0.76–0.91)
65–84 years	Reference	Reference	Reference	Reference	Reference	Reference
85 and over	0.70 (0.62–0.79)	0.33 (0.25–0.43)	1.02 (0.83–1.27)	1.13 (1.08–1.19)	1.26 (1.19–1.34)	1.06 (0.96–1.17)
Gender						
Male	Reference	Reference	Reference	Reference	Reference	Reference
Female	0.89 (0.84–0.95)	0.71 (0.65–0.77)	1.32 (1.13–1.54)	1.29 (1.25–1.33)	1.21 (1.16–1.25)	1.01 (0.96–1.08)
Number of comorbidities						
0	Reference	Reference	Reference	Reference	Reference	Reference
1	4.46 (4.15–4.78)	4.86 (4.41–5.35)	3.32 (2.76–4.00)	1.72 (1.65–1.79)	1.83 (1.74–1.92)	1.42 (1.31–1.54)
2	9.10 (8.32–9.96)	9.07 (8.01–10.27)	7.50 (6.01–9.37)	2.35 (2.20–2.52)	2.59 (2.39–2.80)	1.87 (1.65–2.12)
3	9.52 (8.33–10.88)	8.99 (7.46–10.83)	8.00 (5.78–11.08)	2.77 (2.49–3.07)	3.06 (2.72–3.45)	2.32 (1.93–2.79)
> 3	15.03 (12.69–17.80)	9.67 (7.43–12.59)	13.74 (9.45–20.00)	3.95 (3.41–4.58)	4.65 (3.96–5.46)	3.10 (2.41–3.98)
Injury severity						
Serious injury (ICISS< 0.941)	8.65 (8.14–9.19)	8.15 (7.49–8.87)	2.87 (2.42–3.39)	1.78 (1.71–1.86)	1.98 (1.89–2.08)	1.88 (1.75–2.03)
Other injury (ICISS> = 0.941)	Reference	Reference	Reference	Reference	Reference	Reference
Body region						
Head	Reference	Reference	Reference	Reference	Reference	Reference
Neck	1.44 (1.20–1.73)	0.97 (0.76–1.23)	1.13 (0.63–2.03)	1.00 (0.89–1.13)	1.05 (0.92–1.20)	1.13 (0.90–1.40)
Thorax	2.95 (2.64–3.28)	1.32 (1.13–1.54)	2.41 (1.73–3.35)	1.47 (1.36–1.58)	1.43 (1.31–1.56)	1.29 (1.10–1.50)
Abdomen, lower back, lumbar spine & pelvis	1.23 (1.08–1.40)	0.57 (0.47–0.69)	0.98 (0.65–1.48)	1.67 (1.56–1.79)	1.57 (1.45–1.70)	1.58 (1.38–1.80)
Shoulder & upper arm	0.29 (0.23–0.36)	0.10 (0.07–0.15)	1.01 (0.69–1.48)	1.45 (1.35–1.55)	1.17 (1.08–1.27)	1.60 (1.41–1.81)
Elbow & forearm	0.10 (0.07–0.13)	0.04 (0.02–0.07)	0.91 (0.64–1.29)	1.23 (1.15–1.31)	0.93 (0.86–1.00)	1.38 (1.22–1.55)
Wrist & hand	0.03 (0.02–0.05)	0.02 (0.01–0.03)	0.66 (0.47–0.92)	0.75 (0.70–0.79)	0.58 (0.54–0.63)	0.90 (0.80–1.01)
Hip & thigh	1.46 (1.30–1.63)	0.27 (0.21–0.34)	2.54 (1.92–3.37)	1.92 (1.81–2.04)	1.70 (1.58–1.82)	1.78 (1.59–2.01)
Knee & lower leg	0.24 (0.20–0.29)	0.08 (0.06–0.11)	0.89 (0.64–1.24)	1.11 (1.05–1.18)	0.88 (0.82–0.95)	1.46 (1.31–1.63)
Ankle & foot	0.09 (0.05–0.14)	0.04 (0.02–0.10)	0.42 (0.20–0.87)	1.13 (1.03–1.24)	1.06 (0.95–1.18)	1.77 (1.52–2.06)
Foreign body	0.54 (0.40–0.74)	0.34 (0.22–0.53)	1.27 (0.68–2.38)	0.85 (0.73–0.97)	0.74 (0.62–0.88)	0.58 (0.42–0.81)
Burns	2.15 (1.76–2.64)	1.82 (1.43–2.33)	1.16 (0.54–2.51)	1.57 (1.38–1.80)	1.78 (1.53–2.06)	3.32 (2.75–4.02)

Table 3 Associations between injury outcomes and population groups: results of univariate modelling *(Continued)*

Multiple body regions	0.92 (0.13–6.72)	##	##	2.31 (1.00–5.32)	1.71 (0.60–4.87)	##
Unspecified body region	0.12 (0.03–0.49)	##	##	1.56 (1.22–1.98)	1.22 (0.90–1.65)	0.92 (0.51–1.64)
Body region not relevant	5.39 (4.94–5.90)	3.91 (3.52–4.34)	3.80 (2.90–4.97)	1.58 (1.48–1.69)	1.42 (1.31–1.53)	1.11 (0.97–1.28)
Grouped injury type (first occurring)						
Superficial injury	0.33 (0.25–0.43)	0.57 (0.39–0.85)	0.41 (0.24–0.69)	0.80 (0.74–0.86)	0.88 (0.81–0.97)	0.50 (0.42–0.59)
Open wound	0.18 (0.14–0.22)	0.33 (0.24–0.45)	0.57 (0.43–0.75)	0.63 (0.60–0.66)	0.65 (0.61–0.69)	0.58 (0.52–0.63)
Fracture	Reference	Reference	Reference	Reference	Reference	Reference
Dislocation, sprain & strain	0.12 (0.08–0.17)	0.05 (0.01–0.14)	0.25 (0.14–0.43)	0.57 (0.53–0.61)	0.59 (0.54–0.64)	0.48 (0.41–0.55)
Injury to nerves & spinal cord	1.19 (0.90–1.57)	2.81 (1.98–4.01)	0.51 (0.21–1.23)	0.59 (0.51–0.69)	0.66 (0.54–0.80)	0.55 (0.41–0.74)
Injury to blood vessels	1.66 (1.24–2.21)	3.73 (2.56–5.43)	1.06 (0.50–2.25)	0.54 (0.44–0.66)	0.56 (0.43–0.71)	0.42 (0.28–0.63)
Injury to muscle & tendon	0.08 (0.05–0.14)	0.06 (0.02–0.18)	0.32 (0.18–0.56)	0.51 (0.47–0.55)	0.49 (0.44–0.55)	0.46 (0.39–0.54)
Crushing injury	##	##	##	0.55 (0.37–0.81)	0.47 (0.28–0.81)	0.21 (0.07–0.66)
Traumatic amputation	0.30 (0.17–0.55)	0.92 (0.48–1.79)	0.25 (0.06–1.02)	0.81 (0.69–0.94)	0.73 (0.60–0.89)	0.98 (0.77–1.26)
Eye injury- excluding foreign body	0.36 (0.14–0.97)	0.68 (0.17–2.72)	0.42 (0.06–2.99)	1.45 (1.15–1.82)	1.60 (1.23–2.09)	1.15 (0.75–1.75)
Intracranial injury	4.67 (4.23–5.16)	13.53 (11.80–15.53)	1.27 (0.91–1.79)	0.83 (0.77–0.91)	1.07 (0.98–1.18)	0.75 (0.64–0.87)
Injury to internal organs	14.69 (13.01–16.59)	19.37 (16.12–23.28)	2.17 (1.35–3.51)	1.02 (0.88–1.17)	1.46 (1.25–1.69)	1.05 (0.83–1.34)
Foreign body	0.73 (0.54–1.00)	1.33 (0.85–2.06)	0.86 (0.47–1.57)	0.59 (0.52–0.68)	0.63 (0.53–0.74)	0.33 (0.24–0.46)
Burns	2.90 (2.38–3.54)	7.03 (5.46–9.04)	0.78 (0.37–1.66)	1.11 (0.97–1.26)	1.50 (1.30–1.73)	1.91 (1.60–2.28)
Other and unspecified injury	0.14 (0.10–0.19)	0.25 (0.16–0.39)	0.34 (0.22–0.52)	0.86 (0.81–0.91)	1.00 (0.94–1.07)	0.35 (0.30–0.40)
Systemic-poisoning/toxic effects	7.56 (7.00–8.16)	15.46 (13.69–17.46)	2.63 (2.13–3.23)	1.13 (1.07–1.20)	1.21 (1.13–1.30)	0.61 (0.53–0.70)
Other effects of external cause/ complication	5.02 (4.13–6.10)	11.65 (9.08–14.95)	2.07 (1.16–3.70)	0.97 (0.82–1.15)	1.07 (0.87–1.31)	0.87 (0.64–1.19)
SEIFA						
1	Reference	Reference	Reference	Reference	Reference	Reference
2	0.94 (0.81–1.08)	0.85 (0.69–1.06)	0.39 (0.20–0.76)	1.12 (1.04–1.22)	1.03 (0.93–1.13)	0.97 (0.83–1.12)
3	1.07 (0.94–1.22)	0.93 (0.76–1.13)	2.21 (1.54–3.17)	1.06 (0.98–1.14)	1.01 (0.92–1.11)	1.04 (0.91–1.19)
4	0.85 (0.76–0.96)	0.97 (0.82–1.15)	1.26 (0.88–1.81)	1.08 (1.01–1.15)	1.03 (0.95–1.11)	0.94 (0.84–1.06)
5	0.74 (0.64–0.85)	0.88 (0.72–1.08)	0.94 (0.60–1.48)	0.91 (0.84–0.99)	0.86 (0.78–0.94)	0.88 (0.76–1.01)
6	0.77 (0.67–0.88)	0.98 (0.81–1.18)	1.16 (0.77–1.75)	1.03 (0.96–1.11)	0.99 (0.91–1.08)	1.04 (0.91–1.19)
7	0.74 (0.65–0.85)	0.81 (0.67–0.99)	1.20 (0.80–1.81)	0.97 (0.90–1.05)	0.94 (0.86–1.03)	0.93 (0.81–1.06)
8	0.73 (0.65–0.81)	0.88 (0.75–1.03)	1.70 (1.23–2.34)	1.04 (0.97–1.10)	0.93 (0.87–1.00)	0.94 (0.84–1.05)
9	0.68 (0.61–0.77)	0.75 (0.63–0.88)	1.62 (1.17–2.25)	1.10 (1.03–1.17)	0.92 (0.86–0.99)	0.85 (0.76–0.95)
10	0.65 (0.57–0.73)	0.77 (0.65–0.91)	1.59 (1.14–2.22)	1.13 (1.06–1.20)	0.85 (0.79–0.92)	0.81 (0.72–0.91)
999	##	##	##	##	##	##

Notes
Omitted from analysis due to zero observations with outcome

Table 4 Summary of hospital acquired complications among injury patients, Victoria 2012–13 to 2013–14

Number of complications in CHADx classes			CHADx subclasses with the twenty largest number of CHADx codes		
Class	Description	n (%)	Subclass	Description	n (%)
5	Cardiovascular complications	6755 (13.7)	15.2	Electrolyte disorders w/o dehydration	3158 (6.4)
7	Gastrointestinal complications	6058 (12.3)	5.6	Hypotension	2859 (5.8)
15	Metabolic disorders	6005 (12.1)	10.4	Alterations to mental state	2688 (5.4)
9	Genitourinary complications	5279 (10.7)	7.4	Constipation	2512 (5.1)
17	Other complications	5046 (10.2)	5.3	Cardiac arrythmias, conduction disturbances & abnormal heart beat	2350 (4.8)
6	Respiratory complications	3970 (8.0)	7.5	Nausea and Vomiting	2036 (4.1)
10	Hospital-acquired psychiatric states	3686 (7.5)	14.2	Other hospital-acquired anaemia	1687 (3.4)
1	Intra and post procedural complications	2696 (5.5)	9.2	Urinary tract infection	1660 (3.4)
14	Haematological disorders	2605 (5.3)	9.3	Urinary retention	1574 (3.2)
2	Adverse drug events	2584 (5.2)	6.3	Acute lower respiratory infections (including influenza & pneumonia)	1458 (2.9)
8	Skin conditions	2541 (5.1)	8.3	Dermatitis, rash and other skin effects	1398 (2.8)
3	Accidental injuries	955 (1.9)	15.1	Dehydration/volume depletion	1148 (2.3)
4	Specific infections	692 (1.4)	1.7	Other complications of surgical and Medical care not elsewhere classified (including shock)	1063 (2.2)
16	Nervous system complications	551 (1.1)	9.1	Acute & unspecified kidney failure	1028 (2.1)
11	Early pregnancy complications	0 (0.0)	6.1	Adult respiratory distress syndrome (ARDS), respiratory failure and pulmonary collapse (including atelectasis)	981 (2.0)
12	Labour, delivery & postpartum complications	4 (0.0)	8.1	Pressure injury	957 (1.9)
13	Perinatal complications	13 (0.0)	9.4	Other complications and symptoms of the urinary system	940 (1.9)
			2.16	Adverse effects due to other drugs	935 (1.9)
			15.5	Disorders of mineral metabolism	786 (1.6)
			17.6	Fever (not classified to condition)	769 (1.6)
				All other CHADx subclasses	17,453 (35.3)

Note: Total number of CHADx conditions =49,440

as an appendix with supporting Additional file 1: Tables S1 and S2, as the main focus of this study was to establish the associations between base factors (mostly those present at point of hospital admission) and outcomes.

Discussion

This study described injury outcomes in terms of mortality, complications and burden of hospital-admitted injury patients in Victoria. These outcomes are shown to differ by age, gender, comorbidities, body region injured, injury type and injury severity.

The main finding is that outcomes and risk factors differ depending on the outcome measured, and the method used to measure the outcome. Increasing age was associated with all outcomes. The need for post hospital-discharge care on the other hand was highest among children followed by the 85 and over age group. MV use was more likely to be by those in the 15–64 age group than the 65 and above age group. Gender was only likely to effect complications, LOS and CCU stay (females more likely than males). Severe injuries increased the likelihood of all adverse outcomes.

Increasing number of comorbidities increased the likelihood of all adverse outcomes. Injuries to certain body regions had an increased likelihood of negative outcomes; body regions with notably increased likelihoods of adverse effects varied by outcome. Injury to internal organs, intracranial injury, burns, systematic poisonings, eye injuries and injury to blood vessels were likely to increase adverse outcomes. Comparing outcomes, determining demographic and injury-related factors associated with adverse outcomes and thereby identifying groups at risk can help target secondary and tertiary injury prevention measures.

Numerous other studies [7, 10, 14] have treated age, gender and injury severity as confounders and the findings from our analysis confirm that age and injury severity are risk factors for most of the outcomes measured in this population. Overall, results on age, gender, body region and injury type proportions, LOS and injury severity aligned with previous Australian national statistics [1, 2]. The proportion of injury patients with comorbidities in this study was 19.5% as opposed to a previous research for New South Wales (NSW), Queensland and South Australia [58] which was 15.6%; the difference is likely to be attributable to the fact that this study included 31 conditions as opposed to the 17 CCI conditions used in the other study.

In-hospital death

Our finding that increasing age, injury severity and comorbidities are associated with mortality after injury has been previously documented [5]. The proportion of patients who died in hospital (0.9% of index admissions) in this study is not dissimilar to a reported national proportion of 0.97% for 2005–06, though the latter was not limited to injury and contained more exclusions than ours (excluded palliative care and neonates) [59]. The proportion of 5.0% in-hospital deaths among serious injury patients in this study is close to the 4.4% reported for a severe trauma population for Victoria using data from 1996 to 2001 [21]. These two findings imply that injury patients have a higher rate of in-hospital death over general hospital admitted patients (includes injury and non-injury) and greater injury severity increases the risk. The proportion of deaths-in-hospital for the 85 years and over group (4.4%) is lower than previously published research of 9.5% for a cohort of patients admitted to an academic trauma centre in USA between 2006 and 2010 [17]. The latter cohort consisted of patients 90 years and over, the difference in the age cut-off most likely to contribute to the difference.

Intracranial injury was more likely to result in in-hospital death compared to other injury types, which echoes findings from previous work [17]. This study found that comorbidities had a notable effect on the outcome. There is varied findings on the effect of comorbidity on mortality among injury patients. Some studies also argued that the effect of increasing age and serious injury dominate the outcome over the presence of comorbidities [5, 11, 14, 20, 21, 23, 35, 60]; in other words, these studies [11, 14, 21, 35, 60] concluded that once age and injury severity were adjusted for, the effect of comorbidity was not significant, while others [5, 20, 23] concluded that the effect of comorbidity was significant among patients with minor or moderately severe injuries. The majority of injuries, however, are not severe, and therefore assessing the effects of comorbidity among mild to moderately injured patients is still valuable.

Complications

The findings from this study that age, comorbidities and injury severity increase the likelihood of complications confirms findings of previous research [10]. This study also found associations between body region and injury type with complications. The finding here is novel in revealing information on the effect of patient characteristics on hospital acquired complications for injury patients: increasing age, injury type and severity, and comorbidities all increased the likelihood of hospital-acquired complications.

Discharge destination

This study confirms the finding that injury severity and comorbidities are likely to influence discharge destination [9, 10, 12, 15], but found that gender had no effect; contradicting a finding from a previous study [36]. The difference can be attributed to the fact that the study by Brown et al. (2012) [36] was based on a group of traumatic brain injury patients aged 65 years and over and they categorised patients discharged home with support services as not needing long term care, contrary to our categorisation. They also adjusted for marital status and ethnicity. We found older females to have a higher proportion of being discharged with support services over their male counterparts which could partly explain the findings in the former study. The exclusion of patients who originally came from long-term care institutions has reduced the number of patients needing further care. However, the proportion of such patients was less than 2%; therefore, the impact on the results would have been relatively minor.

Cost

The finding that hospital admission costs for injury patients are associated with injury severity has been reported in previous studies [14, 18]. These studies also found age to be associated with increased costs. The association of costs with comorbidity has also been established

previously [14]. Findings from this study that costs can be higher for patients with lower extremity injuries and injury to blood vessels and internal organs have not been documented in past research. Injuries to lower extremities limit mobility and therefore delay discharge from hospital. This can be observed in the extended LOS for patients with hip and thigh injuries. The extended LOS and possibly major surgeries could be attributable to higher costs for this group of patients. The higher costs associated with injury to blood vessels and internal organs could be attributable to the fact that some of the patients with such injuries were the most likely to have an ICU stay and use the mechanical ventilator.

LOS

Age, injury severity and number of comorbidities were found to be associated with LOS in this study and previous research [14, 35]. Injuries to the lower extremities and trunk were likely to increase LOS, which was confirmed in a former study [14]. The mean hospital LOS of 5.4 days in this Victorian population was higher than the national mean of 3.6 days as reported by Pointer (2018) [2] for injury patients in 2014–15, and the current study does corroborate the finding from Pointer (2018) that females are likely to stay longer in hospital. The longer length of stay in the current study was due to the capture of days in hospital for all subsequent statistical separations and inward transfers due to complications within the index admission. The national report on the other hand picks up all records with an injury in the principal diagnosis but does not identify subsequent statistical separations and transfers as part of one episode. These extra records were captured by the use of data linkage in this study. This reveals that data linkage can provide more accurate estimates of burden. The median LOS of 3–6 days among those aged 65 year and over in the present study aligns well with another study in NSW [18] which reported 5–7 days, the higher LOS in the latter could be explained by the fact that it was solely based on level I trauma centre data.

CCS

Our findings that age, injury severity, comorbidities and body region are associated with ICU and ventilator use was seen in previous work [10, 11, 61]. We did not find any resources with details on CCU use of injury patients to compare, and the low proportion (0.4%) could be the reason that most studies did not focus on this outcome. Factors associated with CCS use are quite different to other outcome measures such as death, cost, LOS and 30-day readmissions. For example, ICU stay or the use of the MV is relatively more common in the 15–64-year age groups whereas the other outcomes are high among the 65 and over age groups. The effect of certain injury types (i.e., intracranial injuries and injuries to internal organs, blood vessels and nerves and spinal cord) is greater on ICU stay and MV use than on other outcomes.

Readmission

This study's finding that age, injury severity and comorbidity are associated with 30-day readmissions is aligned with previous research. The non-planned 30-day readmission proportion of 7.9% in this population is a little higher compared to previous findings of 5.9% for trauma patients aged 16 years and above from a Canadian Provincial Trauma system between 1998 and 2009 [19]. For potentially-avoidable 30-day readmissions, the SQLape methodology was utilised in this study. Potentially-avoidable 30-day readmissions are defined as unforeseen readmissions due to a previously known affection under this methodology. These generally consists of (i) iatrogenic complications, (ii) conditions generally resulting from pre-existing conditions and (iii) preventable diseases like deep vein thrombosis, pulmonary embolism and decubitus ulcer [43]. Since pre-existing conditions (comorbidities) were a factor for consideration in this study, patients with a 30-day readmission outcome with a primary diagnosis indicating it was a complication due to a pre-existing condition were not included. This could have contributed to the drop in this outcome (it has been shown that this quotient of patients account for nearly 80% of potentially-avoidable readmissions [43]). Therefore, this study's use of a limited component of SQLape methodology may not be sufficient to capture the outcome. Finally, even if this component was included, the results may not have been accurate, as per the discussion by Walraven et al., (2011) [62]. They undertook a systematic review of literature on potentially-avoidable readmissions which included the SQLape methodology and stated that though many methods exist for identifying these readmissions, the methods had deficits and the proportions computed using the various methods varied significantly. They concluded that the true proportions of these potentially avoidable readmissions are still unclear.

There is evidence to suggest inter-relationships between outcomes exist; especially the effect of complications on readmissions [19], complications on LOS [33], ventilator use on mortality and cost and LOS [14] and ICU use on readmissions [63]. This study established all the associations mentioned except the association between complications and readmissions which were not significant in this instance. Apart from those noted here, many other associations were also established. Establishing inter-relationships between eleven outcomes is a study strength and this information will be useful in tertiary prevention. For e.g., complications are related to MV use, therefore precautions can be taken to mitigate

complications for patients on the MV. They are also useful in research: one outcome may be used as proxy for another. e.g. LOS as proxy for cost, when cost cannot be measured.

Limitations

Some limitations are noted in this study. We were unable to censor out-of-hospital deaths when selecting 30-day readmission cases, which may have resulted in an under-estimate in 30-day readmissions. We were also unable to estimate the hospital treatment costs for all the patients in the cohort; data on treatment costs were unavailable for private hospitals patients and missing for some of the public hospital patients (around one-fifth in total). Since the discussion of costs in this study is around averages as opposed to totals, we expect that the missing public hospital data would only have a minor impact on the overall conclusions.

Analysis of hospital admissions data does not provide information on all prevalent comorbidities. Coding has relevance for hospital reimbursement, and mostly, only conditions that had an impact on the patient management of the present episode are coded [39]. Validation studies have found that more serious and life-threatening conditions (e.g., cancer) are more likely to be captured in the codes than clinically non-specific and symptomatic conditions (e.g., rheumatologic) [22]; furthermore, coding can be insensitive towards certain conditions such as dementia [64]. Conversely, minor conditions are more likely to get coded among healthier patients as there are no serious ailments to record. Apart from that, in the case of fatalities or long hospital stay, more comorbid conditions are recorded, resulting in higher ORs. Prevalence of comorbidities have been found to be lower in administrative data than in medical records [65] and their clinical severity not recorded [22]. We acknowledge that the use of the U78-U88 codes (supplementary codes for chronic disease identification) incorporated into the VAED since 2015/16 will add value to this work and we propose using these in further research.

The number of complications identified in this study is not a perfect estimate of the total due to: (1) limitations in using hospital administrative databases such as the VAED and (2) limitations of CHADx. Regarding (1): a previous study on the VAED [66] revealed that only 76.2% of admissions were correctly allocated a complication in the 'condition onset' flag, which means that this study could be failing to capture about a quarter of the complications. Regarding (2), the drawback of the CHADx: although it aims to minimise double counting of complications, it has been shown to be less than perfect [67], due to the linear representation of conditions in the diagnosis codes, leaving the possibility for some overestimation of CHADx conditions [67]. For the purpose of providing an overview of injury outcomes in terms of complications, however, we considered the CHADx to be adequate.

Further information on the cause of readmission in the VAED would enable better classification of 30-day readmissions. A former study found that most of the readmissions were due to comorbidity than the index primary diagnosis [26], which states that paying attention to the acute condition of the index disease during the post-discharge period can mar the observation /treatment of comorbidities, resulting in readmissions.

Injury outcomes studies can benefit from including other factors such as marital status [68], ethnicity [16, 69] and insurance status [17]. However, we considered these variables to be non-essential for this descriptive study and therefore they were excluded due to space limitations. Further information on the available facilities and capacities, and the location of the individual hospitals (travel time to get access) can also add value to the prediction of outcomes as these features are likely to contribute. Apart from these, a major limitation of predefined databases is that not all the variables required for a study may be readily available.

Conclusions

This study provides a comprehensive overview of outcomes for hospital-admitted injury patients along with their demographic and injury characteristics; the use of linked data has the advantage of better and longer patient follow-up in administrative data sets.

Similar outcomes when measured in different ways lead to very different results. Most notably, 30-day readmission proportions are higher when considering all-cause 30-day readmission than when considering the non-planned. Proportion of patients requiring mechanical ventilation is half the proportion admitted to the ICU. The magnitude of the effect of certain factors vary between similar outcomes based on how the outcome was measured: the matrix of outcomes vs factors provides meaningful insight into the specific effects of certain patient or injury characteristics on outcomes.

Additional file

Additional file 1: Associations between outcomes. **Table S1.** Associations between outcomes: results of univariate modelling. **Table S2.** Univariate model types used to output Table S1. (DOCX 16 kb)

Abbreviations

AUD: Australian dollars; CCI: Charlson Comorbidity Index; CCS: Critical care services; CCU: Cardiac care unit; CHADx: Classification of Hospital Acquired Diagnoses; CI: Confidence interval; CVDL: Centre for Victorian Data Linkage; ECM: Elixhauser Comorbidity Measure; ICD-10-AM: International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modifications; ICISS: International Statistical Classification of

Diseases based Injury Severity Score; ICU: Intensive care unit; IQR: Interquartile range; IRR: Incident rate ratio; IRSAD: Index of Relative Socio-Economic Advantage and Disadvantage; LOS: Length of hospital stay; MV: Mechanical ventilator; NSW: New South Wales; OR: Odds ratio; SEIFA: Socio-Economic Indexes for Areas; SLA: Statistical Local Areas; SQLape: Striving for Quality Level and Analyzing of Patient Expenses; SRR: Survival risk ratio; VAED: Victorian Admitted Episodes Dataset; VCDC: Victorian Cost Data Collection

Acknowledgements
The authors would like to thank the Centre for Victorian Data Linkage for providing the data and linkage services and Prof. James Harrison at the National Injury Surveillance Unit for providing the SRRs.

Authors' contributions
TF and JB conceived the presented idea, developed the theory, analysed and interpreted the data. SN verified the analytical methods while ZA facilitated data acquisition. JB, SN and ZA supervised TF in producing the findings of this work. All authors read and approved the final manuscript.

Funding
This paper is part of a PhD Thesis which is supported by the Victorian Injury Surveillance Unit funded by the Victorian Government.

Availability of data and materials
The data that support the findings of this study are available from CVDL but restrictions apply to the availability of this data, which were used under license for the current study, and so are not publicly available. The authors are not in a position to release the data (in accordance with the agreement with CVDL).

Ethics approval and consent to participate
The study was approved by the Monash University Human Research Ethics Committee (Project no: 1256). Historical administrative data was used. The research is low risk in that there will be no discomfort or foreseeable risk of harm to the participants. Name, date of birth and other identifiers are removed from the dataset by the data custodian prior to release of the data to the researchers. Due to the magnitude of the dataset, it is impractical to obtain consent. In requesting ethics approval, the reason for not requesting consent was stated, and the committee was satisfied that the proposal meets the requirements of the 'National Statement on Ethical Conduct in Human Research' and granted approval.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

Author details
[1]Monash University Accident Research Centre, Monash University, Clayton Campus, 21 Alliance Lane, Clayton, Victoria 3800, Australia. [2]Victorian Agency for Health Information, 50 Lonsdale Street, Melbourne, Victoria 3000, Australia.

Received: 13 June 2018 Accepted: 30 May 2019
Published online: 21 June 2019

References

1. AIHW:Pointer SC. Trends in hospitalised injury, Australia, 1999–00 to 2010–11. In: *Injury research and statistics series no 86 Cat no INJCAT 162*. Canberra: AIHW; 2013.
2. AIHW:Pointer SC. Trends in hospitalised injury, Australia 1999–00 to 2014–15. In: *Injury research and statistics series no 110 Cat no INJCAT 190*. Canberra: AIHW; 2018.
3. Australian Institute of Health and Welfare. Australian burden of disease study: Impact and causes of illness and death in Australia 2011. In: *Australian burden of disease study series no 3 BOD 4*. vol. 3. Canberra: AIHW; 2016.
4. Moore L, Lavoie A, Sage NL, Bergeron É, Émond M, Liberman M, Abdous B. Using information on preexisting conditions to predict mortality from traumatic injury. Ann Emerg Med. 2008;52(4):356–64 e352.
5. McGwin G Jr, MacLennan PA, Fife JB, Davis GG, Rue LW III. Preexisting conditions and mortality in older trauma patients. J Trauma Acute Care Surg. 2004;56(6):1291–6.
6. Gabbe BJ, Magtengaard K, Hannaford AP, Cameron PA. Is the Charlson comorbidity index useful for predicting trauma outcomes? Acad Emerg Med. 2005;12(4):318–21.
7. Thompson HJ, Rivara FP, Nathens A, Wang J, Jurkovich GJ, Mackenzie EJ. Development and validation of the mortality risk for trauma comorbidity index. Ann Surg. 2010;252(2):370–5.
8. Toson B, Harvey LA, Close JC. The ICD-10 Charlson comorbidity index predicted mortality but not resource utilization following hip fracture. J Clin Epidemiol. 2015;68(1):44–51.
9. Senn-Reeves JN, Jenkins DH. Examining the relationship between preinjury health and injury-related factors to discharge location and risk for injury-associated complications in patients after blunt thoracic trauma: a pilot study. J Trauma Nurs. 2015;22(3):136–47.
10. Ahmad R, Cherry RA, Lendel I, et al. Increased hospital morbidity among trauma patients with diabetes mellitus compared with age- and injury severity score–matched control subjects. Arch Surg. 2007;142(7):613–8.
11. Kao LS, Todd SR, Moore FA. The impact of diabetes on outcome in traumatically injured patients: an analysis of the National Trauma Data Bank. Am J Surg. 2006;192(6):710–4.
12. Lustenberger T, Talving P, Lam L, Inaba K, Bass M, Plurad D, Demetriades D. Effect of diabetes mellitus on outcome in patients with traumatic brain injury: a national trauma databank analysis. Brain Inj. 2013;27(3):281–5.
13. Aggarwal R, Soni KD, Gupta A, Kumar S. Outcome of patients of chest trauma suffering from chronic obstructive pulmonary disease — experience at level 1 trauma Centre. Anaesthesiol Intensive Ther. 2016;48(3):162–5.
14. Kuwabara K, Matsuda S, Imanaka Y, Fushimi K, Hashimoto H, Ishikawa KB, Horiguchi H, Hayashida K, Fujimori K, Ikeda S. Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database. J Trauma Acute Care Surg. 2010;68(2):463–70.
15. Chen AY, Zagorski B, Parsons D, Vander Laan R, Chan V, Colantonio A. Factors associated with discharge destination from acute care after acquired brain injury in Ontario, Canada. BMC Neurol. 2012;12(1):16.
16. Chang P-FJ, Ostir GV, Kuo Y-F, Granger CV, Ottenbacher KJ. Ethnic differences in discharge destination among older patients with traumatic brain injury. Arch Phys Med Rehabil. 2008;89(2):231–6.
17. Hwabejire JO, Kaafarani HA, Lee J, et al. Patterns of injury, outcomes, and predictors of in-hospital and 1-year mortality in nonagenarian and centenarian trauma patients. JAMA Surg. 2014;149(10):1054–9.
18. Curtis K, Chan DL, Lam MK, Mitchell R, King K, Leonard L, D'Amours S, Black D. The injury profile and acute treatment costs of major trauma in older people in New South Wales. Australas J Ageing. 2014;33(4):264–70.
19. Moore L, Lauzier F, Stelfox HT, Le Sage N, Bourgeois G, Clément J, Shemilt M, Turgeon AF. Complications to evaluate adult trauma care: an expert consensus study. J Trauma Acute Care Surg. 2014;77(2):322–30.
20. Morris JA Jr, MacKenzie EJ, Edelstein SL. The effect of preexisting conditions on mortality in trauma patients. JAMA. 1990;263(14):1942–6.
21. Gabbe BJ, Cameron PA, Wolfe R, Simpson P, Smith KL, McNeil JJ. Predictors of mortality, length of stay and discharge destination in blunt trauma. ANZ J Surg. 2005;75(8):650–6.
22. Quan H, Li B, Couris CM, Fushimi K, Graham P, Hider P, Januel J-M, Sundararajan V. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. Am J Epidemiol. 2011;173(6):676–82.
23. Carnilloni L, Farchi S, Rossi PG, Chini F, Borgia P. Mortality in elderly injured patients: the role of comorbidities. Int J Inj Control Saf Promot. 2008;15(1):25–31.
24. Savic G, DeVivo MJ, Frankel HL, Jamous MA, Soni BM, Charlifue S. Causes of death after traumatic spinal cord injury—a 70-year British study. Spinal Cord. 2017;55:891.
25. Fife D. Time from injury to death (survival time) among fatally injured pedestrians. Injury. 1987;18(5):315–8.
26. Donzé J, Lipsitz S, Bates DW, Schnipper JL. Causes and patterns of readmissions in patients with common comorbidities: retrospective cohort study. BMJ. 2013;347:f7171.

27. van Walraven C, Dhalla IA, Bell C, Etchells E, Stiell IG, Zarnke K, Austin PC, Forster AJ. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. CMAJ. 2010;182(6):551–7.
28. Halfon P, Eggli Y, Prêtre-Rohrbach I, Meylan D, Marazzi A, Burnand B. Validation of the potentially avoidable hospital readmission rate as a routine indicator of the quality of hospital care. Med Care. 2006;44(11):972–81.
29. Donzé J, Aujesky D, Williams D, Schnipper JL. Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model. JAMA Intern Med. 2013;173(8):632–8.
30. McIlvennan CK, Eapen ZJ, Allen LA. Hospital readmissions reduction program. Circulation. 2015;131(20):1796–803.
31. Ehsani JP, Jackson T, Duckett SJ. The incidence and cost of adverse events in Victorian hospitals 2003-04. Med J Aust. 2006;184(11):551.
32. Jackson TJ, Michel JL, Roberts RF, Jorm CM, Wakefield JG. A classification of hospital-acquired diagnoses for use with routine hospital data. Med J Aust. 2009;191(10):544.
33. Trentino K, Swain GS, Burrows S, Sprivulis PC, Daly F. Measuring the incidence of hospital-acquired complications and their effect on length of stay using CHADx. Med J Aust. 2013;199:543–7.
34. Moore L, Lauzier F, Stelfox HT, Kortbeek J, Simons R, Bourgeois G, Clément J, Turgeon AF. Validation of complications selected by consensus to evaluate the acute phase of adult trauma care: a multicenter cohort study. Ann Surg. 2015;262(6):1123–9.
35. Bochicchio GV, Joshi M, Bochicchio K, Shih D, Meyer W, Scalea TM. Incidence and impact of risk factors in critically ill trauma patients. World J Surg. 2006;30(1):114–8.
36. Brown SB, Colantonio A, Kim H. Gender differences in discharge destination among older adults following traumatic brain injury. Health Care Women Int. 2012;33(10):896–904.
37. Kilgo PD, Osler TM, Meredith W. The worst injury predicts mortality outcome the best: rethinking the role of multiple injuries in trauma outcome scoring. J Trauma Acute Care Surg. 2003;55(4):599–607.
38. Curtis K, Zou Y, Morris R, Black D. Trauma case management: improving patient outcomes. Injury. 2006;37(7):626–32.
39. Gabbe BJ, Harrison JE, Lyons RA, Edwards ER, Cameron PA. Comparison of measures of comorbidity for predicting disability 12-months post-injury. BMC Health Serv Res. 2013;13(1):1.
40. Australian Institute of Health and Welfare. Admitted patient care 2015–16. In: *Australian hospital statistics health services series no75 Cat no HSE 185*. Canberra: AIHW; 2017.
41. Australian Consortium for Classification Development. The international statistical classification of diseases and related health problems, tenth revision, Australian modification (ICD-10-AM/ACHI/ACS) (Tenth ed.). Darlinghurst: Independent Hospital Pricing Authority; 2012.
42. Potentially avoidable readmissions. http://www.sqlape.com/AR_ALGORITHM.htm. Accessed 13 Mar 2018.
43. Halfon P, Eggli Y, van Melle G, Chevalier J, Wasserfallen J-B, Burnand B. Measuring potentially avoidable hospital readmissions. J Clin Epidemiol. 2002;55(6):573–87.
44. 6401.0 Consumer Price Index, Australia http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6401.0Mar%202018?OpenDocument. Accessed 04 June 2018.
45. Age Standard, 2014, Version 1.7 http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/1200.0.55.006main+features62014,%20Version%201.7. Accessed 15 Mar 2018.
46. Osler T, Rutledge R, Deis J, Bedrick E. ICISS: an international classification of disease-9 based injury severity score. J Trauma Acute Care Surg. 1996;41(3):380–8.
47. Harrison J. Survival risk ratios for Australia; 2008.
48. Australian Institute of Health and Welfare, Henley G, Harrison JE. Injury severity scaling: A comparison of methods for measurement of injury severity. In: *Injury technical paper series no 10*. Canberra: AIHW; 2009.
49. Cryer C, Samaranayaka A, Russell D, Davie G, L J. The epidemiology of serious non-fatal work-related traumatic injury – a demonstration project. In: *Official Statistics Research Series*. Vol. 3. Wellington: Injury Prevention Research Unit, University of Otago; 2008.
50. Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia. 2011. http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/2033.0.55.001~2011~Main%20Features~SEIFA%20Measures~10016. Accessed 04 May.
51. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis. 1987;40(5):373–83.
52. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. Med Care. 1998;36(1):8–27.
53. Quan H, Sundararajan V, Halfon P, Fong A, Burnand B, Luthi J-C, Saunders LD, Beck CA, Feasby TE, Ghali WA. Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data. Med Care. 2005;43(11):1130–9.
54. Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. J Clin Epidemiol. 2004;57(12):1288–94.
55. Lin M, Jr HCL, Shmueli G. Research commentary—too big to fail: large samples and the p-value problem. Inf Syst Res. 2013;24(4):906–17.
56. SAS Institute. SAS software, Version 9.4. Cary: SAS Institute Inc; 2002–2012.
57. StataCorp. Stata Statistical Software: Release 14. College Station: StataCorp LP; 2015.
58. Mitchell RJ, Cameron CM, McClure R. Higher mortality risk among injured individuals in a population-based matched cohort study. BMC Public Health. 2017;17:150.
59. Australian Institute of Health and Welfare, Ben-Tovim D, Woodman R, Harrison JE, Pointer S, Hakendorf P, Henley G. Measuring and reporting mortality in hospital patients. Cat. no. HSE 69. vol. Cat. no. HSE 69. Canberra: AIHW; 2009.
60. Perel P, Arango M, Clayton T, Edwards P, Komolafe E, Poccock S, Roberts I, Shakur H, Steyerberg E. Predicting outcome after traumatic brain injury: practical prognostic models based on large cohort of international patients. BMJ. 2008;336(7641):425–9.
61. Wu J, Sheng L, Ma Y, Gu J, Zhang M, Gan J, Xu S, Jiang G. The analysis of risk factors of impacting mortality rate in severe multiple trauma patients with posttraumatic acute respiratory distress syndrome. Am J Emerg Med. 2008;26(4):419–24.
62. Van Walraven C, Bennett C, Jennings A, Austin PC, Forster AJ. Proportion of hospital readmissions deemed avoidable: a systematic review. CMAJ. 2011;183(7):E391–402. https://doi.org/10.1503/cmaj.101860.
63. Moore L, Stelfox HT, Turgeon AF, Nathens AB, Le Sage N, Émond M, Bourgeois G, Lapointe J, Gagné M. Rates, patterns, and determinants of unplanned readmission after traumatic injury: a multicenter cohort study. Ann Surg. 2014;259(2):374–80.
64. Tonelli M, Wiebe N, Guthrie B, James MT, Quan H, Fortin M, Klarenbach SW, Sargious P, Straus S, Lewanczuk R. Comorbidity as a driver of adverse outcomes in people with chronic kidney disease. Kidney Int. 2015;88(4):859–66.
65. Lee DS, Donovan L, Austin PC, Gong Y, Liu PP, Rouleau JL, Tu JV. Comparison of coding of heart failure and comorbidities in administrative and clinical data for use in outcomes research. Med Care. 2005;43(2):182–8.
66. Jackson TJ, Michel JL, Roberts R, Shepheard J, Cheng D, Rust J, Perry C. Development of a validation algorithm for 'present on admission' flagging. BMC Med Inform Decis Mak. 2009;9(1):48.
67. Michel JL, Nghiem HS, Jackson TJ. Using ICD-10-AM codes to characterise hospital-acquired complications. Health Inf Manag. 2009;38(3):18–25.
68. Spitz G, McKenzie D, Attwood D, Ponsford JL. Cost prediction following traumatic brain injury: model development and validation. J Neurol Neurosurg Psychiatry. 2015;87:173–80.
69. Morris DS, Rohrbach J, Sundaram LMT, Sonnad S, Sarani B, Pascual J, Reilly P, Schwab CW, Sims C. Early hospital readmission in the trauma population: are the risk factors different? Injury. 2014;45(1):56–60.

Publisher's Note

Additional file 1

Associations between outcomes

In-hospital death was likely associated with complications and the use of CCS. Complications were associated with LOS and MV use, which proves what is already known in clinical care. Patients requiring ICU stay or MV use were likely to be discharged with support services. Costs were higher for patients with complications, used CCS or had an in-hospital death. Complications, ICU stay and MV use were likely to increase LOS. Complications and CCU stay were likely to result in an ICU stay or MV use. Complications were also associated with CCU stay. Patients discharged with support services were more likely to have a 30-day readmission against those who were discharged without support services (Table S1). Table S2 presents the model types employed to test significance of associations.

Table S1: Associations between outcomes: results of univariate modelling

Independent \ Dependent	In-hospital death	CHADx complications	Care needed post index admission discharge	Hospital cost of index admission	Length of stay of index admission	ICU stay	MV use	CCU stay	30 day-all-cause readmission	30 day -non-planned readmission	30 day-potentially avoidable readmission
In-hospital death	-	-	-	1.51 (1.44-1.58)*	1.10 (1.03-1.17)	-	-	-	-	-	-
CHADx complications	1.50 (1.48-1.53)*	-	1.23 (1.22-1.24)	0.46 (0.45-0.46)*	0.58 (0.57-0.58)*	1.60 (1.58-1.62)*	1.52 (1.50-1.55)*	1.31 (1.27-1.34)*	1.20 (1.18-1.21)	1.21 (1.19-1.22)	1.23 (1.21-1.24)
Care needed post index admission discharge	-	-	-	-	-	-	-	-	1.76 (1.71-1.82)*	1.60 (1.54-1.67)*	1.73 (1.63-1.84)*
Hospital cost of index admission	-	-	-	-	-	-	-	-	1.04 (1.03-1.06)	1.10 (1.08-1.12)	1.06 (1.03-1.08)
Length of stay of index admission	-	0.04 (0.04-0.04)*	1.02 (1.02-1.02)	0.06 (0.06-0.06)	-	-	-	-	1.01 (1.01-1.01)	1.01 (1.01-1.01)	1.01 (1.01-1.01)
ICU stay> 0 hours	11.16 (9.81-12.69)*	-	1.71 (1.60-1.83)*	1.81 (1.77-1.85)*	1.50 (1.46-1.53)*	-	-	-	1.83 (1.69-1.98)*	2.07 (1.89-2.27)*	1.88 (1.64-2.15)*
MV use > 0 hours	14.88 (12.80-17.29)*	2.16 (2.12-2.21)*	1.86 (1.69-2.04)*	2.04 (1.99-2.09)*	1.65 (1.60-1.71)*	-	-	3.56 (2.50-5.07)*	1.83 (1.63-2.05)*	2.04 (1.79-2.32)*	1.97 (1.62-2.38)*
CCU stay> 0 hours	2.81 (1.71-4.64)*	-	0.90 (0.75-1.08)	0.97 (0.85-1.09)*	1.00 (0.90-1.10)	7.80 (6.41-9.50)*	3.56 (2.50-5.07)*	-	1.78 (1.47-2.17)*	1.95 (1.56-2.44)*	1.50 (1.04-2.17)*
30 day-all-cause readmission	-	-	-	-	-	-	-	-	-	-	-
30 day -non-planned readmission	-	-	-	-	-	-	-	-	-	-	-
30 day-potentially avoidable readmission	-	-	-	-	-	-	-	-	-	-	-

Notes: * Significant associations between two outcomes (effect size of 30% or more)

Table S2: Univariate model types used to output Table S1

Outcome vs outcome	**Outcome type - regression model (test statistic)**
In-hospital death, CCS use, readmissions and discharge destination modelled with each other	Binary vs binary - logistic (OR)
In-hospital death /discharge destination vs complications	Binary vs continuous - logistic (OR)
CCS use vs complications	Binary vs continuous - logistic (OR)
Readmissions vs complications	Binary vs continuous - logistic (OR)
Discharge destination vs LOS	Binary vs continuous - logistic (OR)
Readmissions vs LOS	Binary vs continuous - logistic (OR)
Cost vs in-hospital death/CCS use	Continuous vs binary - log-linear (Beta coefficient)
Costs vs complications/LOS	Continuous vs continuous - log-linear (Beta coefficient)
LOS vs in-hospital death/CCS use	Continuous vs binary - negative binomial (IRR)
LOS vs complications	Continuous vs continuous - negative binomial (IRR)
Readmissions vs ln(cost)	Binary vs continuous - logistic (OR)
Complications vs LOS	Continuous vs continuous - linear (Beta coefficient)
Complications vs MV use	Continuous vs binary - linear (Beta coefficient)

4 Injury comorbidity indices for mortality

This chapter includes a paper which was published in the *Annals of Emergency Medicine*

titled

"The Australian Injury Comorbidity Index (AICI) to predict mortality".

(attached at the end of the chapter)

Fernando DT, Berecki-Gisolf J, Newstead S and Ansari Z (2020a) [54]

The conclusions drawn in the previous chapter along with recommendations from past research are that the associations between comorbidity and outcomes vary depending on the outcome. This implies that in the derivation of comorbidity indices, their relevance to the particular outcome should be considered. The quantification of this also varies by the study population, the types of data available for the quantification of outcomes and comorbidities, prevalence of comorbidities in the specific population and clinical relevance (discussed in Chapter 1).

The most severe adverse outcome for hospital-admitted patients is mortality. This outcome can occur during the hospital stay or post-discharge from hospital. It has been established that outcomes such as in-hospital death, 30-day and 1-year mortality among general hospital-admitted patients are affected by comorbidities [25, 31, 35, 55, 56]. Quantifying the effect of comorbidities on these outcomes is useful for clinical care and epidemiological research.

The CCI, which is a commonly used comorbidity index, was derived for assessing 1-year mortality, while the next most commonly used index, the ECM, was derived for in-hospital death, LOS and costs. However, these indices are used for considering *any* mortality outcome in a range of current research and clinical settings.

Further, as was seen in the literature review in Chapter 1, existing indices such as the CCI and ECM were derived using a general medical population, whereas the same indices have been widely used in specific *injury* populations.

This chapter aimed to derive comorbidity indices that capture the effect of pre-existing comorbidities on the specific outcomes of in-hospital death, 30-day and 1-year mortality for hospital-admitted injury patients. These have been compared with existing indices, and both the new and existing indices were validated in population subgroups and an interstate dataset.

The research questions that will be answered in this chapter are:

1. Based on the analysis of Victorian data:
    a. How can comorbidity best be quantified?
    b. Does an updated comorbidity index perform significantly better than the CCI, updated CCI by Quan et al. and the ECM in predicting injury outcomes?
    c. Do the indices' performance (predictive ability) vary among subgroups of the population?
2. Do the indices developed on Victorian data effectively capture the effect of comorbidity on injury outcomes in other Australian states?

4.1 Summary

In-hospital death, 30-day and 1-year mortality were predicted most strongly by age, gender, injury type and injury severity, and a comorbidity index (regardless of whether they were existing or new) added a fairly small but significant power to a prediction model. Three new binary indices for in-hospital death, 30-day and 1-year

mortality (AICI-hd, AICI-30d and AICI-1yr) were derived. A parsimonious index with comorbidities common to all three *mortality* outcomes was also derived (AICI-m).

A *binary* representation of comorbidities, as distinct from a weighted comorbidity index such as the CCI or the Australian Injury Comorbidity Indices (AICIs) with weights, that only includes conditions significantly associated with the outcome (and is hence more parsimonious than the ECM) can provide *similar* predictive powers as the existing CCI and ECM[4]. This answers questions 1a and 1b: how can comorbidity best be quantified, and do the new indices perform better than the CCI and ECM in terms of mortality outcomes?

In answer to question 1c: do the indices' performance (predictive ability) vary among subgroups of the population (in terms of mortality outcomes), the following was found: the new indices can be reliably applied to children, older adults, non-severe injury, intracranial injury, hip fractures (30-day and 1-year mortality only) and blunt trauma subgroups. The CCI and ECM on the other hand validated well on all of the above subgroups except for hip fractures. In general terms, the existing and new indices performed adequately, with the new indices performing slightly better than the existing indices.

It was found through validation that the AICI-hd is robust enough for use in NSW (i.e. interstate data), while the AICI-30d and AICI-1yr are less robust. The existing CCI

[4] Discussion related to the updated CCI has been omitted to maintain the focus on the original CCI and ECM; the statistics for the updated CCI can be found in the tables in the paper attached to this chapter.

and ECM also performed similarly to the AICIs in NSW, indicating a similar robustness. These findings answer question 2.

4.2 Implications

A set of binary indices capture the individual impact of each comorbidity on specific outcomes equally well as the use of a weighted total score as computed in the CCI. The AICIs are a binary representation similar to the ECM, but include fewer conditions than the ECM, making them easier to use and statistically more viable for use in smaller samples. The new indices consider a more comprehensive list of pre-existing conditions (i.e., a combined list of CCI and ECM conditions compared to the CCI or ECM taken individually) and identifies conditions that are relevant to each outcome among general injury populations. The empirical comorbidity weights derived in this study for each outcome are different to the weights allocated by the CCI. This implies that the effect of comorbidity weights on outcomes are different in the current population compared to the population that the CCI was derived in, and therefore comorbidity indices require periodic review. The AICIs were robust for use among some subgroups of the Victorian injury population while their robustness on interstate populations varied.

The lack of a significant difference between predictive powers of the existing and new indices is attributable to the fact that among injury patients, mortality is driven mostly by age and injury severity rather than comorbidity. Comorbidities are more likely to impact burden and complications outcomes than mortality. Therefore, it should be determined how injury comorbidity indices for burden and complications could improve the predictive ability of baseline models and compare the indices with the CCI

and ECM. The following two chapters derive and validate injury comorbidity indices for burden and in-hospital complications.

The Australian Injury Comorbidity Index to Predict Mortality

D. Tharanga Fernando, BSc(Hons)*; Janneke Berecki-Gisolf, PhD; Stuart Newstead, BSc(Hons), PhD, AStat; Zahid Ansari, MPH, PhD

*Corresponding Author. E-mail: tara.fernando@monash.edu, Twitter: @tharanga361.

Study objective: Existing comorbidity indices such as the Charlson comorbidity index are dated yet still widely used. This study derives and validates up-to-date comorbidity indices for hospital-admitted injury patients, specific to mortality outcomes.

Methods: Injury-related hospital admissions data for 2 cohorts of patients in the Australian state of Victoria were linked to mortality data: July 2012 to June 2014 (161,334 patients) and July 2006 to June 2015 (614,762 patients). Logistic regression models were fitted, and results were used to derive binary and weighted comorbidity indices to predict mortality outcomes. The indices were validated with data from New South Wales (Australia).

Results: There were 11 comorbidity groups identified as associated with inhospital death (cohort 1), 13 with 30-day mortality, and 19 with 1-year mortality (cohort 2). The newly derived weights for comorbidities were very different from the Charlson comorbidity index weights for some conditions. The area under the curve statistics for inhospital death, 30-day mortality, and 1-year mortality were similar for the newly derived binary comorbidity indices (0.920, 0.923, and 0.910, respectively), the Charlson comorbidity index (0.915, 0.919, and 0.906, respectively), and the Elixhauser comorbidity measure (0.924, 0.923, and 0.908, respectively). The false-negative rates for the new binary indices (15.8%, 15.8%, and 16.3%, respectively) were statistically equal to those of the Charlson comorbidity index (17.4%, 16.3%, and 16.5%, respectively) and the Elixhauser comorbidity measure (15.2%, 14.8%, and 16.3%, respectively).

Conclusion: The newly derived Australian Injury Comorbidity Indices, which are a binary representation of individual conditions associated with the outcome of interest, are useful in quantifying the effect of comorbidity among injury patients. They include a shorter list of conditions than existing indices such as the Charlson comorbidity index and Elixhauser comorbidity measure, are up to date, and consider the individual association of each condition over a summed score such as the Charlson comorbidity index. Indices that quantify the effect of comorbidities should consider the population, disease prevalence, and outcome of interest and require periodic updating. [Ann Emerg Med. 2020;75:339-353.]

Please see page 340 for the Editor's Capsule Summary of this article.

Readers: click on the link to go directly to a survey in which you can provide **feedback** to *Annals* on this particular article.
A **podcast** for this article is available at www.annemergmed.com.

0196-0644/$-see front matter

https://doi.org/10.1016/j.annemergmed.2019.10.003

INTRODUCTION

Background

Preexisting comorbidities increase the likelihood of adverse outcomes among patients with an index (primary) disease or injury. Inhospital death,[1-4] 30-day mortality,[1] and 1-year mortality[1,5] among general hospital-admitted patients are affected by comorbidities. Determinants of outcomes of hospital-admitted injury patients are different from those of general hospital-admitted patients: any measures to quantify the effects of comorbidity require specificity to the study population and outcome being investigated.[6-8] Cameron et al[9] found that injury patients were more likely to have chronic diseases than noninjury patients, and Thompson et al[5] indicated a need for an injury-specific comorbidity index. Apart from the study population and outcome, the type of data available for study, as well as the prevalence and clinical importance of specific comorbidities in that population, should also be considered when the effect of comorbidity is quantified. Such measures are useful in clinical care, epidemiologic research, clinical trials, and health care resource administration.[10,11]

Importance

Studies that account for comorbidity commonly use the Charlson comorbidity index,[12] which was derived in 1984. It allocates a weighted summed score for 19 comorbidity groups and was originally derived to assess 1-year mortality

Editor's Capsule Summary

What is already known on this topic

Comorbidities may contribute to outcomes among injured patients and are often included in epidemiologic research.

What question this study addressed

There is a need for an updated comorbidity index that will aid and improve trauma-related outcomes research.

What this study adds to our knowledge

The authors derived and validated a simpler injury comorbidity index that is applicable to trauma mortality predication and research.

How this is relevant to clinical practice

Although not directly applicable to everyday emergency care, this simpler and updated comorbidity index, when applied to injury-related epidemiologic and outcomes research, will help improve trauma patient care.

based on a general hospital-admitted patient cohort. Given the advances in medical science and shifts in chronic disease epidemiology since the derivation of the index, the selection of comorbidities as well as the weights representing the effect magnitude require updating.[1,13] The Charlson comorbidity index was derived only for 1-year mortality, and Toson et al[7] found that although the index was a valid tool for predicting mortality, it did not perform well for predicting resource use after a hip fracture. Furthermore, conditions such as diabetes with complications and severe liver disease may have a pronounced effect on wound recovery (outcome more specific to injury patients); the Charlson comorbidity index is based on mortality among general patients but does not focus on comorbidities that affect wound recovery in particular.

Certain studies that validated the Charlson comorbidity index on injury populations found that the count of comorbidities or a binary indication of comorbidity presence was better than the index,[3,7] whereas others found the index to be a good quantifier of comorbidity effects.[14,15]

Another commonly used comorbidity index (less frequently used than the Charlson comorbidity index, however) is the Elixhauser comorbidity measure.[6] Derived in 1998, the measure is a binary index that considers the presence of 30 comorbidity groups, which includes all but 3 conditions from the Charlson comorbidity index. Some of the major drawbacks of the Elixhauser comorbidity measure are that it requires adjustment for 30 binary covariates, could result in overfitting, and may not work for small samples.

One of the first updates to the Charlson comorbidity index was by Deyo et al (comorbidities condensed to 17 groups),[16] which has been widely used, and the latest update to the Charlson comorbidity index weights was in 2011 by Quan et al,[1] whereas the Elixhauser comorbidity measure was enhanced by van Walraven et al[17] in 2009 into a total score.

Goals of This Investigation

Overall, there is a need for an up-to-date comorbidity measure: a measure with a comprehensive list of comorbidities, yet with a reasonable number of conditions to avoid detecting noise, able to run in small samples, and appropriate for injury populations. This study aimed to derive and validate comorbidity indices that capture the effect of preexisting comorbidities on selected mortality outcomes. The outcomes are inhospital death, 30-day mortality, and 1-year mortality for hospital-admitted injury patients.

MATERIALS AND METHODS

This was a retrospective analysis of injury-related hospital admissions data linked with mortality data in the states of Victoria and New South Wales, Australia. The Victorian and New South Wales data were used as derivation and validation data sets, respectively. Data provision and linkage were undertaken by the Centre for Victorian Data Linkage in Victoria and the Centre for Health Record Linkage in New South Wales.

Morbidity data were extracted from the Victorian Admitted Episodes Dataset for Victoria and the Admitted Patient Data Collection for New South Wales, both of which contain unit records of all public and private hospital admissions. These data sets contain patient demographics and morbidity information, which includes 40 diagnosis fields for Victoria and 51 for New South Wales. These fields contain disease, injury, and external-cause data, coded to the *International Statistical Classification of Diseases and Related Health Problems, 10th Revision, Australian Modification (ICD-10-AM)*.[18] Information on inhospital deaths was extracted from the Victorian Admitted Episodes Dataset and Admitted Patient Data Collection, whereas 30-day and 1-year mortality were extracted from the Registrar of Births, Deaths and Marriages records in Victoria and New South Wales.

Data linkage was performed by the Centre for Victorian Data Linkage with deterministic data linkage, with some fuzzy matching to allow for slight variation in the linkage variables such as incorrect names and dates. The center used probabilistic matching of identifiers such as name, address, date of birth, and sex. The center estimates the false-positive rates to be between approximately 0.5% and 1% (personal communication, James Harrison, Flinders University, 2018), and the Centre for Health Record Linkage estimates them to be 0.5%.[19] Both estimate the false-negative rate to be lower than the false-positive one.

Injury cases were selected with a protocol established for national reporting in Australia,[20] being records with *ICD-10-AM* diagnosis codes in the range S00 to T75 or T79 in the first diagnosis field. Case selection, which was limited to residents in each state, was based on the index injury (defined as the first injury record in the morbidity data set for a patient during the study period). Consecutive records of inward transfers from other hospitals or changes in care type within the same hospital were considered to be part of one episode.

Two patient cohorts were selected for each state: one for observing inhospital death (cohort 1) and the other for 30-day and 1-year mortality (cohort 2).

The first cohort included patients with an index injury admission between July 1, 2012, and June 30, 2014 (161,334 patients in Victoria and 233,521 in New South Wales). With internally linked data within the morbidity data set, patients were followed up for all subsequent hospital admissions for 1 year. The follow-up was to establish the patient discharge status at the end of the index episode; this included inhospital death, transfer, and change in care type. When the comorbidity index was derived, patients who died within 24 hours of admission were excluded because they had a low probability of survival most likely to be attributable to a non-survivable injury. Patients who stayed longer than 365 days or were palliative-care patients were also excluded. Children (<15 years) were excluded because this group is heterogeneous to the rest of the cohort, given the low prevalence of comorbidity in this age group.

The cohorts of patients with an index injury admission in the morbidity data were followed up in the mortality data of the relevant state. Cases were extracted as follows: for Victoria patients admitted from July 1, 2006, to June 30, 2015, followed up for 30 days and 1 year (614,762 patients), and for New South Wales patients admitted from July 1, 2008, to June 30, 2015, followed up for 30 days and 1 year (705,963 patients). When comorbidity indices were derived, children (<15 years) (low prevalence of comorbidity in the group) and patients who died within 24 hours of admission were once again excluded.

Inhospital death and 30-day and 1-year mortality were coded as binary outcomes. The factors considered were age, sex, injury type, injury severity, body region of injury, socioeconomic status, geographic region, and country of birth. Patients were classified into 6 age groups. Injury severity was calculated with the *ICD*-based Injury Severity Score.[21] The survival risk ratios required for the computation of *ICD*-based Injury Severity Scores were sourced from the National Injury Surveillance Unit (personal communication, James Harrison, Flinders University, 2018). With the worst-injury method,[22] a serious injury was considered to be one with an *ICD*-based Injury Severity Score less than or equal to 0.941 (survival probability of 94.1%).[23] Geographic regions were classified as metropolitan and regional, using the local government area of residence in both states. Socio Economic Indexes for Areas–Index of Relative Socio-Economic Advantage and Disadvantage expressed as state-deciles[24] was used to classify the socioeconomic status.

Comorbidities selected for this analysis were a combination of the Charlson comorbidity index[12] and Elixhauser comorbidity measure[6] comorbidity groups according to Quan et al[25] and Sundararajan et al.[26] Thirty-four comorbidity groups were selected, out of which weight loss and fluid-electrolyte disorders (both considered likely to be complications or symptoms, rather than diseases) and other neurologic disorders (which were too diverse a collection of conditions to be grouped) were excluded.

Primary Data Analysis

Correlations between comorbidities were tested with the Pearson's correlation coefficient. Multivariable logistic regression modeling was used to establish the association between comorbidities and outcomes. Various forms of representing comorbidity in the regression models were tested: the presence of at least one comorbidity, count of comorbidities, and a binary representation of each comorbidity. A backward elimination process was carried out to identify comorbidities most associated with the outcome, starting with 31 conditions and eliminating 1 at a time. Models were compared with the Akaike information criterion.[27] A difference of less than 10 between 2 Akaike information criteria indicates that the model with the additional factors provides no further improvement to the model fit. Best predictive power was assessed with discrimination (area under the receiver operating characteristic curve [ROC]) and classification tables. The area under the curve (AUC) ranges from 0 to 1, with less

than 0.7 representing poor discrimination and anything greater than that considered as good discrimination. The significance of differences between AUC statistics was assessed with confidence intervals (CIs); overlapping CIs were considered as an indication of no difference between 2 AUCs. Classification tables were derived on the basis of maximizing the sensitivity and specificity, setting this as the cut-off point for classifying cases predicted by the models. Tests of proportions were carried out to assess the difference between false negatives, with a significance level of 5%.

Next, weights were computed with the model used for the binary index. Weights were computed for each comorbid condition with the resulting odds ratios (ORs) for each condition. The following rules were applied in allocating weights: the condition was dropped from the index if OR<1.2, 1.2≤OR<1.5 resulted in a score of 1, 1.5≤OR<2.5=2, 2.5≤OR<3.5=3, and so on. These weights were summed to create the weighted injury comorbidity index. Five models were compared for best predictive ability. These models were baseline (included only sociodemographic and injury factors) with comorbidity indicated as follows: binary representation, weighted summed score, Charlson comorbidity index, updated Charlson comorbidity index,[1] and Elixhauser comorbidity measure. This process was carried out for each of the 3 outcomes: inhospital death, 30-day mortality and 1-year mortality.

Finally, the new indices, Charlson comorbidity index, and Elixhauser comorbidity measure were validated on the New South Wales data set (with the same baseline models as for Victoria), using the AUC statistic and classification tables. Stata (version 14.0; StataCorp, College Station, TX) was used to analyze the data.[28]

The study was approved by the Monash University Human Research Ethics Committee and the New South Wales Population and Health Services Research Ethics Committee.

RESULTS

In cohort 1, 1.0% of patients died in the hospital (n=1,572), whereas in cohort 2, 0.8% died within 30 days (n=4,911) and 3.0% (n=18,525) died within 1 year of the injury onset (Table 1) (inhospital death spanned a length of stay of 1 to 365 days, whereas 30-day mortality spanned between 1 and 30 days). An overview of comorbidity prevalence by demographic and injury characteristics is provided in Table 1 and Table E1 (available online at http://www.annemergmed.com) (for Victoria) and Table E2 (available online at http://www.annemergmed.com) (for New South Wales).

Correlations between comorbidity groups were below 0.5 for all conditions except between cerebrovascular disease and hemiplegia/paraplegia (0.5) and metastatic solid tumor and any malignancy (0.7) (data not shown). Alcohol dependence, cardiac arrhythmia, dementia, depression, diabetes, and hypertension without complications were the most commonly recorded comorbidities in both cohorts (Table 2). HIV/AIDS, hypertension with complications, moderate to severe liver disease, and obesity displayed high odds of inhospital death but did not provide considerable contribution to model fit, most likely because of low prevalence in this cohort. Malignancies, metastatic solid tumors, chronic obstructive pulmonary disease, congestive heart failure, dementia, liver diseases, myocardial infarction, and renal diseases displayed higher odds of all mortality outcomes.

The multivariable regression modeling results are presented in Table 3. Model 1 is the baseline model for each outcome. The factors included in the baseline models for each outcome are listed in the footnotes for Table 3. All baseline models had excellent predictive power (AUC approximately 0.9), indicating that factors such as age, sex, injury type, and severity are potent predictors of outcomes of injury patients, regardless of comorbidity. Areas under the ROC curves are provided in Appendix E1 (available online at http://www.annemergmed.com) and interaction plots in Appendix E2. Models 2 to 7 are the baseline models with comorbidity added, using newly derived indices or existing indices; results from modeling other forms of indices are provided in Table E3 (available online at http://www.annemergmed.com). The risk-adjusted ORs and suggested weights for the outcomes are presented in Table 4. A model's predictive power was assessed with the model performance statistic (namely, the AUC), whereas model fit was assessed with the Akaike information criterion statistic. A detailed discussion of the results can be found in Appendix E3 (available online at http://www.annemergmed.com), whereas a summary of that discussion is presented next.

According to the lowest Akaike information criteria, the best fit was found in model 6 (containing the Elixhauser comorbidity measure), followed by model 10 (containing all 31 comorbidities), model 11 (containing 11 selected comorbidities with actual weights), and model 2 (containing the Australian Injury Comorbidity Index for inhospital death). The poorest fit in terms of the Akaike information criterion was model 4 (containing the Charlson comorbidity index). Model performance was evaluated with the AUC statistics; the CIs for the AUCs for all the models overlapped, which implied that regardless of which comorbidity measure was used, there was no

Table 1. Characteristics of the study populations.

	Patients Admitted*							
	July 2012 to June 2014, Victoria (Cohort 1)				July 2006 to June 2015, Victoria (Cohort 2)			
Demographic and Injury Characteristics	**No.**	**%**	**At Least 1 Comorbidity (%)**	**Count of Comorbidities, Mean (95% CI)**	**No.**	**%**	**At Least 1 Comorbidity (%)**	**Count of Comorbidities, Mean (95% CI)**
Total patients			161,334				614,762	
Age, y								
0–14	21,240	13.2	1.4	0.01 (0.01–0.02)	99,746	16.2	1.0	0.01 (0.01–0.01)
15–24	23,213	14.4	9.9	0.12 (0.11–0.12)	104,370	17.0	10.6	0.12 (0.12–0.13)
25–44	36,262	22.5	13.0	0.16 (0.16–0.17)	152,633	24.8	12.7	0.16 (0.16–0.16)
45–64	30,799	19.1	19.3	0.25 (0.25–0.26)	117,116	19.1	14.6	0.20 (0.20–0.20)
65–84	31,390	19.5	35.9	0.54 (0.53–0.54)	94,645	15.4	27.4	0.44 (0.44–0.45)
≥85	18,430	11.4	40.0	0.62 (0.60–0.63)	46,252	7.5	36.6	0.58 (0.57–0.59)
Sex								
Men†	89,144	55.3	16.8	0.24 (0.23–0.24)	356,287	58.0	12.6	0.18 (0.18–0.18)
Women	72,190	44.7	23.5	0.33 (0.33–0.34)	258,475	42.0	18.0	0.26 (0.26–0.26)
Injury severity‡								
Serious injury (ICISS<0.941)	20,884	12.9	40.6	0.64 (0.63–0.65)	66,135	10.8	34.4	0.56 (0.55–0.56)
Other injury (ICISS≥0.941)	140,450	87.1	16.7	0.22 (0.22–0.23)	548,627	89.2	12.5	0.17 (0.17–0.17)
Inhospital death§	1,572	1.0	68.2	1.32 (1.26–1.38)				
30-day mortality‖					4,911	0.8	58.5	1.12 (1.09–1.16)
1-y mortality‖					18,525	3.0	50.3	0.92 (0.90–0.93)

ICISS, *ICD*-based Injury Severity Score.
*Index admissions to all public and private hospitals, limited to residents of Victoria with community injuries.
†Intersex patient count less than 5 was added to the majority sex group to protect confidentiality.
‡Worst-injury method: *ICD*-based Injury Severity Score less than or equal to 0.941 was considered serious injury.
§Excludes death within 24 hours of index admission, length of stay greater than 365 days, and palliative care patients (n=161,054).
‖Excludes patients who died within 24 hours of index admission (n=613,856).

significant difference in model performance. However, the baseline model had a lower range for the AUC CI than all the models with a comorbidity measure, indicating that the addition of comorbidity indices to the baseline improved the model performance significantly.

The best fit in terms of the lowest Akaike information criterion statistic for 30-day mortality was model 11 (containing 13 selected comorbidities with actual weights), followed by model 10 (containing all 31 comorbidities), model 2 (containing the Australian Injury Comorbidity Index for 30-day mortality), and model 6 (containing the Elixhauser comorbidity measure), and the poorest fit was model 4 (containing the Charlson comorbidity index). The performance of all these models except the baseline was similar in terms of the AUC statistics, whereas the baseline had a significantly lower range for the AUC CI.

The best fitting in terms of the lowest Akaike information criterion was model 10 (containing all 31 comorbidities), followed by model 2 (containing the Australian Injury Comorbidity Index for 1-year mortality), whereas models containing the existing indices such as the Elixhauser comorbidity measure (model 4) and Charlson comorbidity index (model 6) resulted in much higher Akaike information criteria, implying a poorer fit to the former two. Once again, model performance was similar for the new and existing indices because the CIs for the AUCS for all these models overlapped (except for the baseline model, whose CIs were much lower). This implies that adding comorbidity measures to the baseline significantly improved the model performance but there was no significant difference between type of comorbidity measures for model performance.

The fact that the model performances were the same (ie, AUCs for the Australian Injury Comorbidity Indexes overlapped with those of the full model [with all 31 comorbidities] and existing indices such as the Charlson

Table 2. Presence of comorbidity and the association with selected mortality measures (Victoria, aged 15 years and older).

	Outcome							
		Inhospital Death*			30-Day Mortality†		1-Year Mortality†	
Comorbidity	Cohort 1 (N=139,816), No. (%)	% With Condition Who Had the Outcome	Adjusted OR‡ (95% CI)	Cohort 2 (N=514,139), No. (%)	% With Condition Who Had the Outcome	Adjusted OR‡ (95% CI)	% With Condition Who Had the Outcome	Adjusted OR‡ (95% CI)
HIV/AIDS	54	§	2.81 (0.37–21.11)	141	§	5.30 (1.85–15.16)	5.7	3.08 (1.43–6.66)
Alcohol dependence	6,411 (4.6)	0.7	0.82 (0.59–1.14)	26,704 (5.2)	0.5	0.85 (0.70–1.02)	2.1	1.12 (1.01–1.23)
Drug dependence	1,494 (1.1)	0.7	1.65 (0.85–3.21)	4,864 (0.9)	0.5	1.65 (1.07–2.53)	1.8	2.16 (1.72–2.72)
Any malignancy	690 (0.5)	18.8	5.15 (3.64–7.27)	1,635 (0.3)	16.4	3.21 (2.53–4.08)	54.3	6.63 (5.67–7.75)
Blood loss anemia	170 (0.1)	6.5	1.20 (0.62–2.34)	319 (0.1)	4.4	0.80 (0.45–1.42)	16.0	0.98 (0.70–1.39)
Cardiac arrhythmia	3,748 (2.7)	6.1	1.51 (1.28–1.77)	9,176 (1.8)	6.0	1.44 (1.30–1.59)	16.8	1.35 (1.26–1.44)
Cerebrovascular disease	595 (0.4)	8.2	1.39 (0.94–2.04)	1,675 (0.3)	8.1	1.67 (1.33–2.10)	18.9	1.32 (1.11–1.56)
Chronic pulmonary disease	1,289 (0.9)	8.0	2.42 (1.92–3.05)	2,757 (0.5)	7.4	2.15 (1.83–2.53)	21.9	2.15 (1.94–2.39)
Coagulopathy	1,119 (0.8)	6.7	1.89 (1.44–2.49)	2,202 (0.4)	8.0	2.36 (1.97–2.83)	16.8	1.62 (1.42–1.85)
Congestive heart failure	1,236 (0.9)	13.9	2.70 (2.21–3.29)	2,598 (0.5)	13.7	2.38 (2.08–2.72)	35.4	2.27 (2.06–2.50)
Deficiency anemia	578 (0.4)	4.2	0.81 (0.52–1.27)	1,198 (0.2)	5.2	1.06 (0.80–1.40)	20.3	1.43 (1.21–1.68)
Dementia	2,870 (2.1)	6.8	1.67 (1.41–1.98)	8,985 (1.7)	9.8	2.47 (2.27–2.68)	31.5	2.73 (2.59–2.87)
Depression	2,964 (2.1)	0.7	1.00 (0.62–1.60)	11,312 (2.2)	0.6	0.83 (0.64–1.09)	2.7	1.19 (1.04–1.36)
Diabetes with chronic complications	4,220 (3.0)	4.5	1.13 (0.93–1.37)	10,843 (2.1)	4.0	1.06 (0.93–1.21)	13.8	1.19 (1.10–1.29)
Diabetes without complications	8,939 (6.4)	2.2	1.18 (1.00–1.38)	12,382 (2.4)	2.3	1.07 (0.94–1.22)	8.9	1.17 (1.08–1.25)
Hemiplegia/paraplegia	531 (0.4)	6.8	1.60 (1.03–2.48)	1,354 (0.3)	6.4	1.39 (1.05–1.84)	15.7	1.44 (1.18–1.76)
Hypertension complicated	52	19.2	3.46 (1.60–7.49)	74	§	0.55 (0.18–1.67)	20.3	0.82 (0.43–1.58)
Hypertension uncomplicated	4,484 (3.2)	6.2	1.15 (0.97–1.36)	14,682 (2.9)	4.5	0.95 (0.85–1.06)	14.1	0.91 (0.85–0.97)
Hypothyroidism	152 (0.1)	§	0.43 (0.13–1.41)	357 (0.1)	3.6	0.89 (0.49–1.62)	11.5	0.80 (0.56–1.15)
Metastatic solid tumor	368 (0.3)	22.6	2.75 (1.78–4.26)	794 (0.2)	22.5	3.85 (2.85–5.20)	68.3	5.41 (4.30–6.81)
Mild liver disease	1,162 (0.8)	3.1	2.88 (1.89–4.38)	1,855 (0.4)	3.2	2.29 (1.65–3.17)	10.4	2.89 (2.39–3.51)
Moderate or severe liver disease	107 (0.1)	10.3	4.21 (1.90–9.31)	219	12.3	4.84 (2.83–8.29)	30.6	5.73 (3.86–8.50)
Myocardial infarction	245 (0.2)	18.8	2.67 (1.85–3.88)	842 (0.2)	12.9	1.89 (1.50–2.38)	31.6	1.82 (1.54–2.15)
Obesity	229 (0.2)	3.1	2.38 (1.02–5.54)	1,111 (0.2)	3.1	1.84 (1.25–2.71)	8.1	1.34 (1.04–1.72)

Peptic ulcer disease	83 (0.1)	13.3	8.58 (3.95–18.64)	224 (0.0)	4.9	1.82 (0.94–3.51)	14.3	1.82 (1.18–2.80)
Peripheral vascular disease	701 (0.5)	3.0	1.52 (0.94–2.45)	1,819 (0.4)	4.3	1.78 (1.38–2.30)	12.5	1.59 (1.35–1.87)
Psychoses	567 (0.4)	1.6	2.12 (1.02–4.41)	1,760 (0.3)	1.0	1.21 (0.73–2.00)	4.7	1.95 (1.52–2.50)
Pulmonary circulation disorders	133 (0.1)	9.8	1.35 (0.68–2.68)	316 (0.1)	9.5	1.48 (0.97–2.27)	27.2	1.87 (1.39–2.52)
Renal disease including renal failure	3,369 (2.4)	8.7	2.11 (1.76–2.53)	5,320 (1.0)	9.8	2.04 (1.82–2.29)	28.6	2.13 (1.97–2.29)
Rheumatic disease including some other connective tissue disorders	177 (0.1)	2.8	1.44 (0.57–3.59)	439 (0.1)	2.3	0.87 (0.45–1.71)	10.3	1.16 (0.82–1.63)
Valvular disease	325 (0.2)	10.5	1.59 (1.06–2.39)	829 (0.2)	6.5	0.89 (0.65–1.21)	20.0	0.99 (0.82–1.21)

*Excludes death within 24 hours of index admission, length of stay greater than 365 days, and palliative care patients (n=139,816).
†Excludes patients who died within 24 hours of index admission (n=514,139).
‡All 31 comorbidities modeled simultaneously with the baseline model.
§Cell count 1 to 4 (or proportions resulting from) suppressed to protect confidentiality.

comorbidity index and Elixhauser comorbidity measure) implies that using the new indices (Australian Injury Comorbidity Index for inhospital death, 30-day mortality, and 1-year mortality) with binary representations of the selected conditions will yield a similar predictive power compared with using the existing or full models. One advantage of using the new models is they use only comorbidities relevant to the outcomes, whereas the older indices or the full model includes conditions not relevant to the outcomes. The new indices also provide a better fit in terms of the Akaike information criteria than the Charlson comorbidity index for all 3 outcomes and a better fit than the Elixhauser comorbidity measure for 30-day and 1-year mortality. The new indices also use lesser conditions than the Elixhauser comorbidity measure and retain an equal predictive power, and are better than the baseline model for capturing comorbidity when predicting these outcomes.

Apart from AUCs and Akaike information criteria, false-negative rates are also particularly important in mortality prediction. False negatives in this instance are the number of nondeaths predicted by the model among patients who would actually incur a death. In clinical settings, the false-negative rates should be minimized to ensure that patients likely to incur death are not classified as unlikely to die.

The models using the binary index to quantify comorbidity performed well for all 3 outcomes, with good predictive power (AUC 92.0%, 92.3%, and 91.0% for inhospital death, 30-day mortality, and 1-year mortality, respectively). The false-negative rates were 15.8%, 15.8%, and 16.3% (Table 5) for the binary index for inhospital death, 30-day mortality, and 1-year mortality, respectively, whereas they were 17.4%, 16.3%, and 16.5% for the Charlson comorbidity index and 15.2%, 14.8%, and 16.3% for the Elixhauser comorbidity measure, respectively. Overall, the false-negative rates for the new binary indices were statistically equal to those of the Charlson comorbidity index and Elixhauser comorbidity measure. Although there were no significant differences in false-negative rates between the new indices and the existing ones, in regard to the actual number of patients misclassified, the new indices performed better than the Charlson comorbidity index and not as well as the Elixhauser comorbidity measure. Considering the drawbacks of the wide Elixhauser comorbidity measure index, the new indices can be recommended as the more practical option. Detailed classification tables with the false-negative rates, etc, for the main models are shown in Table E4 (available online at http://www.annemergmed.com).

Discussion on interaction effects, the advantages of the new binary indices over weighted indices, comorbidity indices derived with all age groups (ie, children included),

Table 3. Performance of selected model-fitting strategies in assessing the effect of comorbidity on selected outcome measures (Victoria).

	Inhospital Death*		30-Day Mortality†		1-Year Mortality‡	
Model	**AUC (95% CI)**	**Model Fit AIC**	**AUC (95% CI)**	**Model Fit AIC**	**AUC (95% CI)**	**Model Fit AIC**
(1) Baseline model	0.894 (0.888–0.900)	13,274	0.908 (0.905–0.912)	41,745	0.896 (0.894–0.898)	114,621
(2) Baseline model+individual comorbidity (selected) (binary representation)	0.920 (0.915–0.925)	12,458	0.923 (0.920–0.926)	39,939	0.910 (0.908–0.911)	109,065
(3) Baseline model+comorbidity using integer weights	0.919 (0.914–0.924)	12,467	0.923 (0.920–0.926)	39,939	0.909 (0.907–0.911)	109,153
(4) Baseline model+comorbidity using CCI weights	0.915 (0.909–0.920)	12,675	0.919 (0.916–0.922)	40,543	0.906 (0.904–0.908)	110,810
(5) Baseline model+comorbidity using Quan[1] weights	0.915 (0.910–0.921)	12,645	0.920 (0.917–0.923)	40,274	0.908 (0.906–0.910)	109,704
(6) Baseline model+comorbidity using ECM	0.924 (0.919–0.929)	12,371	0.923 (0.920–0.925)	40,193	0.908 (0.906–0.910)	109,962
(7) Baseline model+comorbidity common to all 3 outcomes (10 conditions) (binary representation)	0.920 (0.915–0.925)	12,478	0.922 (0.919–0.925)	40,013	0.909 (0.907–0.911)	109,327

AIC, Akaike information criterion; *CCI*, Charlson comorbidity index; *ECM*, Elixhauser comorbidity measure.
See Table 4 for selected comorbidities for each outcome.
*Baseline model for inhospital death includes age, sex, injury severity, and injury type.
†Baseline model for 30-day mortality includes age, sex, injury severity, injury type, body region, socioeconomic indexes for areas deciles, geographic region (metropolitan Melbourne and rural Victoria), and country of birth.
‡Baseline model for 1-year mortality includes age, sex, injury severity, injury type, body region, socioeconomic indexes for areas deciles, geographic region (metropolitan Melbourne and rural Victoria), and country of birth.

and comorbidity indices derived with only the older adults (≥65 years), as well as a detailed discussion of the validations, is presented in Appendix E3 (available online at http://www.annemergmed.com).

A binary index (model 7) (Table 3) that includes 10 conditions common to the indices for all 3 outcomes was also derived. These conditions are shown in Table 4. There was no significant difference between predictive powers (AUC) of the individual binary indices and the parsimonious index. The model fit was superior in the individual binary indices (Akaike information criteria=12,458, 39,939, and 109,065 for inhospital death, 30-day mortality, and 1-year mortality, respectively) compared with the parsimonious index (Akaike information criteria=12,478, 40,013, and 109,327, respectively). Tests of proportions revealed that the false-negative rates were not different in the individual binary indices compared with the parsimonious index (inhospital death 15.8% for the individual binary index versus 15.9% for the parsimonious index; 30-day mortality 15.8% versus 16.0%, respectively; and 1-year mortality 16.3% versus 16.4%, respectively). Given these results, the parsimonious index can be used for research without much compromise in classification accuracy. From a clinical perspective, in which the false-negative rates translate into actual patient numbers, the slightly greater false-negative rate of the parsimonious index is a disadvantage (Table 5). Instructions on how to use the new indices are provided in Appendix E4 (available online at http://www.annemergmed.com [Tables AA.1 and AA.2]).

In comparison of the conditions included in the newly derived indices and existing ones, HIV/AIDS had no bearing on this study population as opposed to having a very high weight in the Charlson comorbidity index and updated Charlson comorbidity index (6 and 4, respectively), and diabetes and rheumatic disease had no bearing as opposed to weights of 1 to 2 in the Charlson comorbidity index (Table 4). Hemiplegia/paraplegia earned weights only among long-term (1-year) but not short-term mortality indices. Weights for conditions such as malignancies, dementia, myocardial infarction, and liver diseases were higher in the newly derived weighted indices than in the Charlson comorbidity index and updated Charlson comorbidity index.

The newly derived indices were also tested on specific subgroups of the Victorian study population. The groups were children (≤14 years), older adults (>64 years), nonsevere injuries, intracranial injuries, hip fractures

Table 4. Risk-adjusted ORs and suggested weights for inhospital death, 30-day mortality, and 1-year mortality (derived for Victoria).

	Outcome							
	Inhospital Death		30-Day Mortality		1-Year Mortality			
Key Demographic and Injury Characteristics	OR (95% CI)	Injury Comorbidity Index Weight	OR (95% CI)	Injury Comorbidity Index Weight	OR (95% CI)	Injury Comorbidity Index Weight	CCI	Updated CCI per Quan et al[‡]
Age, y								
0–14	0.06 (0.03–0.10)		0.05 (0.04–0.06)		0.02 (0.02–0.03)			
15–24	0.12 (0.09–0.16)		0.12 (0.10–0.14)		0.06 (0.06–0.07)			
25–44	0.23 (0.18–0.30)		0.21 (0.19–0.24)		0.16 (0.15–0.17)			
45–64	1 (Reference)		1 (Reference)		1 (Reference)			
65–84	2.08 (1.85–2.34)		2.77 (2.59–2.97)		3.24 (3.13–3.36)			
≥85								
Female sex	0.60 (0.54–0.67)		0.66 (0.62–0.70)		0.71 (0.68–0.73)			
Serious injury	4.07 (3.52–4.70)		3.58 (3.27–3.93)		2.06 (1.96–2.16)			
Comorbidity								
HIV/AIDS	–	–	–	–	2.23 (1.78–2.80)	2	6	4
Alcohol dependence	5.08 (3.60–7.17)	5	3.21 (2.53–4.08)	3	6.66 (5.69–7.79)	7	*	*
Drug dependence	–	–	–	–	–	–	*	*
Any malignancy[†]	1.54 (1.31–1.81)	2	1.44 (1.30–1.60)	1	1.35 (1.26–1.44)	1	2	2
Blood loss anemia	–	–	1.88 (1.55–2.29)	2	–	–	*	*
Cardiac arrhythmias[†]	2.44 (1.93–3.08)	2	2.17 (1.85–2.55)	2	2.17 (1.95–2.41)	2	*	*
Cerebrovascular disease	1.97 (1.51–2.58)	2	2.37 (1.98–2.84)	2	1.62 (1.42–1.85)	2	1	0
Chronic obstructive pulmonary disease[†]	2.77 (2.28–3.37)	3	2.42 (2.12–2.76)	2	2.28 (2.07–2.50)	2	1	1
Coagulopathy[†]	–	–	–	–	1.43 (1.22–1.68)	1	*	*
Congestive heart failure[†]	1.68 (1.42–1.98)	2	2.46 (2.26–2.68)	2	2.72 (2.58–2.87)	3	1	2
Deficiency anemia	–	–	–	–	–	–	*	*
Dementia[†]	–	–	–	–	1.14 (1.06–1.22)[‡]	–	1	2
Depression	–	–	–	–	1.17 (1.09–1.26)[‡]	–	*	*
Diabetes with chronic complications	–	–	–	–	1.70 (1.44–2.01)	2	2	1
Diabetes without complications	–	–	–	–	–	–	1	0
Hemiplegia/paraplegia	–	–	–	–	–	–	2	2
Hypertension complicated	–	–	–	–	–	–	*	*
Hypertension uncomplicated	2.74 (1.77–4.24)	3	3.83 (2.84–5.17)	4	5.36 (4.26–6.74)	5	*	*
Hypothyroidism	3.37 (2.29–4.95)	3	2.33 (1.69–3.21)	2	3.03 (2.51–3.67)	3	*	*
Metastatic solid tumor[†]	–	–	4.52 (2.65–7.72)	5	5.99 (4.04–8.87)	6	6	6
Mild liver disease[†]	2.91 (2.02–4.19)	3	1.88 (1.50–2.37)	2	1.78 (1.51–2.11)	2	1	2
Moderate or severe liver disease	–	–	–	–	–	–	3	4
Myocardial infarction[†]	8.58 (3.97–18.56)	9	–	–	–	–	1	0
Obesity	–	–	1.82 (1.41–2.35)	2	1.59 (1.35–1.87)	2	*	*

Table 4. Continued.

Key Demographic and Injury Characteristics	Outcome							
	Inhospital Death		30-Day Mortality		1-Year Mortality			
	OR (95% CI)	Injury Comorbidity Index Weight	OR (95% CI)	Injury Comorbidity Index Weight	OR (95% CI)	Injury Comorbidity Index Weight	CCI	Updated CCI per Quan et al[‡]
Peptic ulcer disease	–	–	–	–	1.95 (1.52–2.51)	2	1	0
Peripheral vascular disease	–	–	–	–	1.90 (1.41–2.55)	2	1	0
Psychoses	2.41 (2.08–2.80)	2	2.05 (1.84–2.28)	2	2.09 (1.94–2.25)	2	*	*
Pulmonary circulation disorders	–	–	–	–	–	–	*	*
Renal disease including renal failure[†]	–	–	–	–	–	–	2	1
Rheumatic disease including some other connective tissue disorders	0.06 (0.03–0.10)	–	0.05 (0.04–0.06)	–	0.02 (0.02–0.03)	–	1	1
Valvular disease	0.12 (0.09–0.16)	–	0.12 (0.10–0.14)	–	0.06 (0.06–0.07)	–	*	*

– Indicates condition not significant in the index.
*Not included in the CCI list.
[†]Common to all 3 outcomes.
[‡]Excluded from weighted index as OR<1.2.

among individuals aged 45 years and older, and blunt trauma (see Table E5 [available online at http://www.annemergmed.com] for model results and Table 5 for false-negative rates). The false-negative rates were high for individuals aged 65 years and older for all outcomes. To address this, a new set of binary and parsimonious indices was derived for all 3 outcomes for this group (see Table E5 for model results [available online at http://www.annemergmed.com], Table 5 for false-negative rates, and Appendix E4 [available online at http://www.annemergmed.com {Table AA.3}] for conditions included). The age-specific indices were able to reduce the false-negative rates only for inhospital death and had no ability to affect the other 2 outcomes (Table 5) (also described under age-comorbidity interaction effects).

Summary statistics for the validation cohort (patient data from New South Wales) are available in Table E2 and E6 (available online at http://www.annemergmed.com). The validation results are available in Table E7 (available online at http://www.annemergmed.com). Overall, the new indices performed just as well as the Charlson comorbidity index and the Elixhauser comorbidity measure in terms of the AUC statistic. In terms of model fit (Akaike information criterion statistic), the binary indices and the parsimonious index outperformed the existing indices, except for inhospital death, in which the Elixhauser comorbidity measure had the best model fit. New South Wales data provided results similar to those of the Victorian data. This confirms the findings from the Victorian data on an external data set, thereby demonstrating the robustness of the new injury comorbidity indices.

Table E8 (available online at http://www.annemergmed.com) presents a snapshot of the comorbidities included in each of the newly derived Australian injury comorbidity indices, the Charlson comorbidity index, and the Elixhauser comorbidity measure.

LIMITATIONS

The present study has several limitations. There was omission of lookback periods to identify comorbidities.[7,29] Lookback periods are a span preceding the current episode, in which records from other hospital admissions for the same patient are retrospectively assessed to identify comorbidities (not mentioned in the current record). However, the expectation for the use of the injury comorbidity indices is not solely for research but also for clinical settings; namely, at point of hospital admission, during which assessing comorbidities from past records is not always feasible and the focus is on capturing current and relevant comorbidities.

Table 5. False-negative rates for various indices by outcome in population subgroups.

Outcome	No. of Patients in Initial Cohort	No. (%) of Patients Who Died	No. (%) of Patients Classified as Not Dying When Likely to Die			
			Outcome-Specific Binary Index	Parsimonious Index	CCI	ECM
Adults (≥15 y), all injuries						
Inhospital death	139,816	1,564 (1.1)	247 (15.8)	249 (15.9)	272 (17.4)	237 (15.2)
30-day mortality	514,139	4,886 (1.0)	770 (15.8)	781 (16.0)	797 (16.3)	723 (14.8)
1-y mortality	514,139	18,475 (3.6)	3,011 (16.3)	3,027 (16.4)	3,039 (16.5)	3,018 (16.3)
Children (<15 y), all injuries						
Inhospital death	257	8 (0.04)	1 (14.3)	1 (14.3)	3 (37.5)	3 (42.8)
30-day mortality	99,717	25 (0.03)	2 (9.1)	3 (13.6)	2 (8.0)	1 (4.6)
1-y mortality	99,717	50 (0.05)	12 (24.0)	13 (26.0)	11 (22.0)	12 (24.0)
≥65 y						
Inhospital death	49,613	1,417 (2.9)	471 (33.2)	474 (33.5)	373 (26.3)	326 (23.0)
Inhospital death (age-group specific)			318 (22.4)	319 (22.5)		
30-day mortality	140,349	4,309 (3.1)	1,253 (29.0)	1,259 (29.3)	1,322 (30.7)	1,269 (29.5)
30-day mortality (age-group specific)			1,261 (29.3)	1,238 (28.7)		
1-y mortality	140,349	16,559 (11.8)	5,761 (34.8)	5,866 (35.4)	5,991 (36.2)	5,829 (35.2)
1-y mortality (age-group specific)			5,700 (34.4)	5,802 (35.0)		
Adults with nonsevere injuries						
Inhospital death	119,851	522 (0.4)	98 (18.8)	98 (18.8)	94 (18.0)	87 (16.7)
30-day mortality	452,036	1,970 (0.4)	320 (16.2)	316 (16.0)	326 (16.6)	301 (15.3)
1-y mortality	452,036	10,830 (2.4)	1,493 (13.8)	1,707 (15.8)	1,750 (16.2)	1,721 (15.9)
Adults with intracranial injury*						
Inhospital death	5,350	244 (4.6)	56 (23.0)	56 (23.0)	57 (23.4)	53 (21.7)
30-day mortality	20,396	710 (3.5)	135 (19.0)	136 (19.2)	139 (19.6)	136 (19.2)
1-y mortality	20,396	1,295 (6.4)	240 (18.5)	237 (18.3)	251 (19.4)	242 (18.7)
Patients ≥45 y with hip fractures†						
Inhospital death	7,956	522 (6.6)	257 (49.2)	262 (50.2)	230 (44.0)	232 (44.4)
30-day mortality	23,459	1,499 (6.4)	517 (34.5)	513 (34.2)	584 (39.0)	573 (38.2)
1-y mortality	23,459	4,470 (19.1)	1,547 (34.6)	1,574 (35.2)	1,662 (37.2)	1,718 (38.4)
Adults with blunt trauma‡						
Inhospital death	94,475	1,408 (1.5)	229 (16.6)	228 (16.2)	223 (15.8)	237 (16.8)
30-day mortality	340,524	4,275 (1.3)	711 (16.6)	713 (16.7)	761 (17.8)	740 (17.3)
1-y mortality	340,524	16,130 (4.7)	2,839 (17.6)	2,822 (17.5)	2,867 (17.8)	2,873 (17.8)
New South Wales validation (≥15 y)						
Inhospital death	201,151	2,292 (1.1)	385 (16.8)	385 (16.8)	399 (17.4)	387 (16.9)
30-day mortality	601,136	8,210 (1.4)	1,534 (18.7)	1,555 (18.9)	1,539 (18.8)	1,509 (18.4)
1-y mortality	601,136	34,041 (5.7)	6,230 (18.3)	6,259 (18.4)	6,331 (18.6)	6,245 (18.4)

Cut-off for classification tables was set to maximize sensitivity and specificity.
*Intracranial injury—*ICD-10-AM* codes S0600 to S0699.
†Hip fractures—*ICD-10* codes S72.0 to S72.2.
‡Blunt trauma—*ICD-10* codes V00 to V99, W00 to W19, W20 to W24, W30 to W31, W50 to W52, X50, X79 to X82, Y00 to Y05, Y29 to Y32, and Y85.

Comorbidity recording can be biased, depending on each patient's profile (ie, patients with life-threatening conditions are likely to have them recorded, whereas the less severe, nonspecific conditions could be ignored). Conversely, for the more healthy patients, the less severe conditions will be recorded as those that are the most visible for this group.

There are limitations inherent in using administrative data. Some studies have found the prevalence of comorbidities to be lower in administrative data than in

medical chart review,[30,31] whereas others have reported that there was no notable difference.[32,33] One of the latter studies was based on a population with acute trauma in Victoria, in which an institution-specific administrative data set, which captures details similar to those in the Victorian Admitted Episodes Dataset and much more, was compared with medical records. Therefore, we consider that using administrative admissions data rather than chart reviews in our Victorian study most likely had no significant influence on the findings while offering a great practical advantage. Another potential disadvantage of administrative data is that coding can be tailored to hospital reimbursement. This can lead to the inclusion of only those conditions that have an effect on patient management of the present episode (other comorbid conditions may not be brought to light).[34] The current study provides an index that is largely robust to this problem because the results were validated on an interstate data set that is likely to have different coding practices and incentives. Nonetheless, administrative data are a useful data source because they have less recall bias, are fully coded, are not resource intensive, and allow the analysis of an entire population over a selected sample. The number of diagnosis codes allowed for in hospital data sets will also determine the capture of comorbidities.

Another limitation is that death records used in this study did not include deaths occurring outside Victoria. Given the limited follow-up period since patient discharge from a Victorian hospital, however, the number of interstate deaths is likely to be low.

The Multipurpose Australian Comorbidity Scoring System[35] is not one of the most widely used indices, and this study was focused on the widely used indices and their performance in injury populations. The Multipurpose Australian Comorbidity Scoring System is more cumbersome to use, given it has 102 conditions instead of the 10 to 19 conditions in the Australian Injury Comorbidity Indexes, and it was not derived with a cohort of injury patients, therefore warranting this study, which derives injury-specific indices.

Furthermore, care should be taken when the newly derived indices are used in populations in which the injury profile or the comorbidity prevalence is likely to be significantly different from that in our derivation and validation populations. For example, there could be underreporting in hospital records of conditions such as obesity, or injury could be more common in a demographic that is associated with lower obesity rates (eg, cyclists, young persons). The newly derived indices, the existing indices, and the specific indices for the group aged 65 years or older have all shown high false-negative rates, indicating that some specific aspects of this group's outcome prediction are driven by factors not included in the present study. In older injury populations, further research is required to identify other influential factors before creation of predictive models.

Another aspect to be mindful of when using these indices is that they should not be used for comparing specific patient outcomes within and between sites because they were not derived with adjustments for the quality of care at each site. The level of care and facilities at each site is expected to affect the 30-day mortality (if not the very short-term and long-term mortality); therefore, the indices will need validation taking the quality of care metric into consideration before use in comparison studies. Furthermore, the proportion with the mortality outcomes among patients with penetrating injuries was smaller than among those with blunt injuries (data not shown). Therefore, the indices are likely to better capture the effects of comorbidity among patients with blunt trauma over penetrating trauma.

Finally, because of the large sample sizes, significance tests were not carried out to evaluate the individual associations between a comorbidity and the outcome. The associations were established with the Akaike information criterion statistic to compare models with and without the comorbidity. Although the latter method is not as conclusive as the former, we were able to establish reasonable associations.

DISCUSSION

This study derived indices to capture the effect of comorbidity on inhospital death, 30-day mortality, and 1-year mortality. Three individual indices and a more parsimonious index were derived, all of which capture and are limited to only those conditions that have an effect on the outcome of interest. Inhospital death, 30-day mortality, and 1-year mortality were mainly predicted by age, sex, injury type, and injury severity, and a comorbidity index adds a fairly small (but significant) predictive power. Although an injury comorbidity index for mortality may not improve prediction of mortality to a great extent (as shown in this study), it is still important in epidemiology. Epidemiologic research requires adjustments for comorbidity to account for variation in case mix and its effect on outcomes. This study provided robust and updated indices for future work applicable to Australian hospital-admitted injury populations.

This study captured the effect of comorbidity on 3 specific mortality outcomes, focusing on prognostic predictability, ease of use, inclusion of conditions with

relevance to the outcomes, and applicability to the patient group of interest. The shorter lists of conditions included in the new indices will use fewer resources in settings in which data have to be collected specifically for this purpose.

The study demonstrated that the effect of comorbid conditions on mortality outcomes varied with the type of mortality outcome considered: conditions that affected inhospital death were different and fewer than conditions that affected 30-day and 1-year mortality, signifying the need for outcome-specific indices. The study also showed that considering an amalgamated list of comorbidities was beneficial. Apart from the conditions listed in the Charlson comorbidity index, comorbidities from the Elixhauser comorbidity measure list such as drug dependence, cardiac arrhythmia, coagulopathy, deficiency anemias, and psychoses had an effect on 1-year mortality, whereas cardiac arrythmia and coagulopathy had an effect on 30-day mortality. Myocardial infarction and dementia were 2 conditions from the Charlson comorbidity index that contributed to the indices that were not in the Elixhauser comorbidity measure list. Therefore, the indices derived in this study are more comprehensive than those in the Charlson comorbidity index or Elixhauser comorbidity measure lists considered individually.

Another important outcome of this study is the index for all mortality outcomes, which provides a measure that can be applied across 3 mortality outcomes without loss in predictive ability.

This study considered the significance of the association between each condition and the outcome, which is important in creating a valid index. Reasonable associations between each condition and the specific outcome were identified. The newly derived binary indices and weighted indices are restricted to conditions effectively contributing to the outcome and represent current disease epidemiology, whereas studies that use the Charlson comorbidity index are compelled to use all 17 of its conditions regardless of their current effect on the outcome. For example, HIV/AIDS did not contribute toward a considerable improvement to model fit in any of the 3 mortality outcomes in the new indices. The strong effect of HIV/AIDS on mortality in the Charlson comorbidity index was valid around 1984 (when the Charlson comorbidity index was derived), but current antiretroviral treatment has made this condition no longer fatal; this is reflected in our results, in which HIV/AIDS had no measurable effect on the outcomes considered in this study. The updated version of the Charlson comorbidity index has found this effect to be lower than in the original Charlson comorbidity index, decreasing from 6 to 4,[1] but our study showed no effect. This could also be attributed to the nature of the study population (injury patients) and low recorded HIV/AIDS prevalence, thereby further relaying the importance of study-specific indices.

An example of the importance of selecting diseases relevant to the outcome can be observed in the weights derived for peptic ulcer disease. It earned a high weight of 9 in the weighted index for inhospital death but had no bearing on 30-day or 1-year mortality in our study; this was in contrast to the weight of 1 assigned in the Charlson comorbidity index.[12] Peptic ulcer disease, when recorded as a comorbidity inhospital, may indicate relatively severe disease with a high risk of potentially fatal gastrointestinal bleeding, whereas in the interim or long term, this condition would be resolved before 30-day and 1-year mortality occurs (ie, nonsevere peptic ulcer disease is relatively common and often treatable).

The only study that derived empirical weights for injury in the past was based on 6 comorbidities in a serious-injury population, concluding that the performance of both their new index and the Charlson comorbidity index was similar and that neither was sufficient at predicting mortality.[5] Other studies with updated Charlson comorbidity index weights were not focused on injury patients.[1,36-38] Given the noted limited generalizability of existing research, the new indices will be useful in injury epidemiology.

The Australian Injury Comorbidity Indexes, developed and validated in general injury patient cohorts, will be a valuable tool for future injury research. These indices, which are binary representations of conditions, are sufficient to adjust for the effects of comorbidity on mortality outcomes without the cumbersome application of weights. Because the associated conditions differ with each outcome measure, the use of unique indices for each outcome will provide a more reliable risk classification of patients in clinical settings. The concise (parsimonious) index developed in this study is recommended for use in epidemiologic research because the one index can be used for predicting short- and long-term mortality, making it a more versatile tool. It can also be used in triage decisions for patients with mild or moderately severe injuries.

The lack of a large difference in the performance of the newly derived indices and the existing Charlson comorbidity index, updated Charlson comorbidity index, and the Elixhauser comorbidity measure is due to the fact that death in injury populations is largely predicted by the baseline model (ie, age and injury severity). We anticipate that if new indices for other outcomes such as burden and complications were derived, they might outperform the Charlson comorbidity index to a greater extent, mainly

because it was developed for assessing mortality, and comorbidities may play a greater role in burden and complication outcomes than in mortality.

Finally, this study derived comorbidity indices with population-based data, provides a novel validation of the new indices, and validates existing indices such as the Charlson comorbidity index and Elixhauser comorbidity measure on a large cohort of general injury patients, and was also tested in subpopulation groups.

In summary, this study recommends the use of a set of binary indices that capture the individual effect of each comorbidity on specific outcomes as opposed to the use of a total score as computed in the Charlson comorbidity index. The new indices are a binary representation similar to the Elixhauser comorbidity measure but include fewer conditions, making them easier to use and statistically more feasible for use in smaller patient cohorts. The new indices consider a more comprehensive list of preexisting conditions (ie, a combined list of Charlson comorbidity index and Elixhauser comorbidity measure conditions compared with the Charlson comorbidity index and Elixhauser comorbidity measure taken individually) and identify conditions that are relevant to each outcome among general injury populations. Compared with the Charlson comorbidity index, these study-specific indices were less likely to predict survival in patients who subsequently died. The empirical comorbidity weights derived in this study for each outcome are different from those weights allocated by the Charlson comorbidity index. This implies that the effect of a comorbidity weighs differently according to the population and outcome, and requires periodic updating.

The authors acknowledge the Centre for Victorian Data Linkage and Centre for Health Record Linkage for providing the data and linkage services, and James Harrison, MBBS, at the National Injury Surveillance Unit for providing the survival risk ratios.

Supervising editor: Robert D. Welch, MD, MS. Specific detailed information about possible conflict of interest for individual editors is available at https://www.annemergmed.com/editors.

Author affiliations: From the Monash University Accident Research Centre, Monash University, Clayton, Victoria, Australia (Fernando, Berecki-Gisolf, Newstead); the Victorian Injury Surveillance, Unit Monash University, Clayton (Berecki-Gisolf); and the Victorian Agency for Health Information, Melbourne, Victoria, Australia (Ansari).

Author contributions: DTF and JB-G conceived the presented idea, developed the theory, and analyzed and interpreted the data. SN verified the analytical methods. ZA facilitated data acquisition. JB-G, SN, and ZA supervised DTF in producing the findings of this work. All authors read and approved the final article. DTF takes responsibility for the paper as a whole.

All authors attest to meeting the four ICMJE.org authorship criteria: (1) Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND (2) Drafting the work or revising it critically for important intellectual content; AND (3) Final approval of the version to be published; AND (4) Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Funding and support: By *Annals* policy, all authors are required to disclose any and all commercial, financial, and other relationships in any way related to the subject of this article as per ICMJE conflict of interest guidelines (see www.icmje.org). The authors have stated that no such relationships exist. This article is part of a PhD thesis that is supported by the Victorian Injury Surveillance Unit, funded by the Victorian government.

Publication dates: Received for publication March 24, 2019. Revisions received June 14, 2019; August 19, 2019, and September 20, 2019. Accepted for publication October 2, 2019. Published online January 16, 2020.

REFERENCES

1. Quan H, Li B, Couris CM, et al. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. *Am J Epidemiol*. 2011;173:676-682.
2. Morris JA Jr, MacKenzie EJ, Edelstein SL. The effect of preexisting conditions on mortality in trauma patients. *JAMA*. 1990;263:1942-1946.
3. Moore L, Lavoie A, Sage NL, et al. Using information on preexisting conditions to predict mortality from traumatic injury. *Ann Emerg Med*. 2008;52:356-364.e352.
4. McGwin G Jr, MacLennan PA, Fife JB, et al. Preexisting conditions and mortality in older trauma patients. *J Trauma Acute Care Surg*. 2004;56:1291-1296.
5. Thompson HJ, Rivara FP, Nathens A, et al. Development and validation of the Mortality Risk for Trauma Comorbidity Index. *Ann Surg*. 2010;252:370-375.
6. Elixhauser A, Steiner C, Harris DR, et al. Comorbidity measures for use with administrative data. *Med Care*. 1998;36:8-27.
7. Toson B, Harvey LA, Close JC. The *ICD-10* Charlson comorbidity index predicted mortality but not resource utilization following hip fracture. *J Clin Epidemiol*. 2015;68:44-51.
8. Yurkovich M, Avina-Zubieta JA, Thomas J, et al. A systematic review identifies valid comorbidity indices derived from administrative health data. *J Clin Epidemiol*. 2015;68:3-14.
9. Cameron CM, Purdie DM, Kliewer EV, et al. Differences in prevalence of pre-existing morbidity between injured and non-injured populations. *Bull World Health Organ*. 2005;83:345-352.
10. Feinstein AR. The pre-therapeutic classification of co-morbidity in chronic disease. *J Chronic Dis*. 1970;23:455-468.
11. Valderas JM, Starfield B, Sibbald B, et al. Defining comorbidity: implications for understanding health and health services. *Ann Fam Med*. 2009;7:357-363.
12. Charlson ME, Pompei P, Ales KL, et al. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis*. 1987;40:373-383.

13. Needham DM, Scales DC, Laupacis A, et al. A systematic review of the Charlson comorbidity index using Canadian administrative databases: a perspective on risk adjustment in critical care research. *J Crit Care*. 2005;20:12-19.
14. Kuwabara K, Matsuda S, Imanaka Y, et al. Injury Severity Score, resource use, and outcome for trauma patients within a Japanese administrative database. *J Trauma Acute Care Surg*. 2010;68:463-470.
15. Neuhaus V, King J, Hageman MG, et al. Charlson comorbidity indices and in-hospital deaths in patients with hip fractures. *Clin Orthop Relat Res*. 2013;471:1712-1719.
16. Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with *ICD-9-CM* administrative databases. *J Clin Epidemiol*. 1992;45:613-619.
17. van Walraven C, Austin PC, Jennings A, et al. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. *Med Care*. 2009;47:626-633.
18. Australian Consortium for Classification Development. *The International Statistical Classification of Diseases and Related Health Problems, 10th Revision, Australian Modification (ICD-10-AM/ACHI/ACS)*. 10th ed. Darlinghurst, Australia: Independent Hospital Pricing Authority; 2012.
19. Centre for Health Record Linkage. Master linkage key quality assurance. 2012. Available at: http://www.cherel.org.au/media/24160/qa_report_2012-a.pdf. Accessed January 8, 2020.
20. Pointer SC; Australian Institute of Health and Welfare. *Trends in Hospitalised Injury, Australia, 1999-00 to 2010-11*. Canberra, Australia: AIHW; 2013; Injury Research and Statistics Series No. 86.
21. Osler T, Rutledge R, Deis J, et al. ICISS: An *International Classification of Disease–9* based Injury Severity Score. *J Trauma Acute Care Surg*. 1996;41:380-388.
22. Henley G, Harrison JE; Australian Institute of Health and Welfare. *Injury Severity Scaling: A Comparison of Methods for Measurement of Injury Severity*. Canberra, Australia: AIHW; 2009; Injury Technical Paper Series No. 10.
23. Cryer C, Samaranayaka A, Russell D, et al. *The Epidemiology of Serious Non-fatal Work-Related Traumatic Injury—A Demonstration Project*. Wellington, New Zealand: Injury Prevention Research Unit, University of Otago; 2008; Official Statistics Research Series. Vol 3.
24. Australian Bureau of Statistics. *Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia*. Canberra, Australia: Australian Bureau of Statistics; 2011.
25. Quan H, Sundararajan V, Halfon P, et al. Coding algorithms for defining comorbidities in *ICD-9-CM* and *ICD-10* administrative data. *Med Care*. 2005;43:1130-1139.
26. Sundararajan V, Henderson T, Perry C, et al. New *ICD-10* version of the Charlson comorbidity index predicted in-hospital mortality. *J Clin Epidemiol*. 2004;57:1288-1294.
27. Akaike H. A new look at the statistical model identification. *IEEE T Automat Contr*. 1974;19:716-723.
28. StataCorp. *Stata Statistical Software: Release 14*. College Station, TX: StataCorp LP; 2015.
29. Preen DB, Holman CDAJ, Spilsbury K, et al. Length of comorbidity lookback period affected regression model performance of administrative health data. *J Clin Epidemiol*. 2006;59:940-946.
30. Lee DS, Donovan L, Austin PC, et al. Comparison of coding of heart failure and comorbidities in administrative and clinical data for use in outcomes research. *Med Care*. 2005;43:182-188.
31. Stavem K, Hoel H, Skjaker SA, et al. Charlson comorbidity index derived from chart review or administrative data: agreement and prediction of mortality in intensive care patients. *Clin Epidemiol*. 2017;9:311-320.
32. Nguyen TQ, Simpson PM, Braaf SC, et al. Comparison of the performance of mental health, drug and alcohol comorbidities based on *ICD-10-AM* and medical records for predicting 12-month outcomes in trauma patients. *BMC Health Serv Res*. 2018;18:408.
33. Price J, Estrada CA, Thompson D. Case study. *Am J Med Qual*. 2003;18:38-45.
34. Gabbe BJ, Harrison JE, Lyons RA, et al. Comparison of measures of comorbidity for predicting disability 12-months post-injury. *BMC Health Serv Res*. 2013;13:1.
35. Holman CAJ, Preen DB, Baynham NJ, et al. A multipurpose comorbidity scoring system performed better than the Charlson index. *J Clin Epidemiol*. 2005;58:1006-1014.
36. Klabunde CN, Potosky AL, Legler JM, et al. Development of a comorbidity index using physician claims data. *J Clin Epidemiol*. 2000;53:1258-1267.
37. Ghali WA, Hall RE, Rosen AK, et al. Searching for an improved clinical comorbidity index for use with *ICD-9-CM* administrative data. *J Clin Epidemiol*. 1996;49:273-278.
38. Schneeweiss S, Wang PS, Avorn J, et al. Improved comorbidity adjustment for predicting mortality in Medicare populations. *Health Serv Res*. 2003;38:1103-1120.

Table E1: Injury characteristics of the study population (continued from Table 1)

	Patients admitted							
	July 2012 to June 2014, Victoria (Cohort 1)				July 2006 to June 2015, Victoria (Cohort 2)			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients	161334				614762			
Grouped body region								
Head/face/neck	32052	19.9	19.2	0.26 (0.25-0.27)	132139	21.5	15.0	0.20 (0.19-0.20)
Trunk	20730	12.8	25.0	0.36 (0.35-0.37)	70589	11.5	17.9	0.27 (0.26-0.27)
Upper extremity	54549	33.8	9.8	0.12 (0.12-0.13)	217859	35.4	6.4	0.09 (0.09-0.09)
Lower extremity	41528	25.7	22.8	0.34 (0.33-0.35)	144438	23.5	16.3	0.26 (0.25-0.26)
Multiple body regions	53	0.0	18.9	0.25 (0.09-0.40)	301	0.0	12.3	0.16 (0.11-0.22)
Unspecified body region	585	0.4	22.6	0.31 (0.26-0.37)	2827	0.5	14.0	0.20 (0.18-0.22)
Body region not relevant	11837	7.3	47.7	0.66 (0.65-0.68)	46609	7.6	45.7	0.63 (0.62-0.63)
Grouped injury type (First occurring)								
Superficial injury	8055	5.0	23.8	0.34 (0.32-0.35)	29094	4.7	16.9	0.23 (0.22-0.24)
Open wound	22398	13.9	14.8	0.19 (0.18-0.20)	91386	14.9	11.1	0.14 (0.14-0.15)
Fracture	66686	41.3	19.6	0.29 (0.28-0.29)	245322	39.9	13.7	0.21 (0.21-0.21)
Dislocation, sprain & strain	10989	6.8	8.2	0.10 (0.10-0.11)	43398	7.1	4.8	0.06 (0.06-0.07)
Injury to nerves & spinal cord	2038	1.3	10.4	0.13 (0.11-0.14)	7641	1.2	8.4	0.11 (0.10-0.12)
Injury to blood vessels	1347	0.8	11.5	0.15 (0.12-0.17)	4827	0.8	10.8	0.14 (0.13-0.15)
Injury to muscle & tendon	8451	5.2	9.1	0.11 (0.10-0.12)	29783	4.8	5.9	0.08 (0.07-0.08)
Crushing injury	335	0.2	3.3	0.04 (0.01-0.06)	1418	0.2	2.3	0.03 (0.02-0.04)
Traumatic amputation	1612	1.0	7.3	0.08 (0.07-0.10)	7177	1.2	4.2	0.05 (0.05-0.06)

Eye injury- excluding foreign body	512	0.3	16.4	0.22 (0.17-0.27)	3476	0.6	8.2	0.11 (0.09-0.12)
Intracranial injury	6416	4.0	29.4	0.43 (0.41-0.45)	24670	4.0	24.1	0.34 (0.33-0.35)
Injury to internal organs	1762	1.1	23.5	0.32 (0.29-0.35)	6863	1.1	19.4	0.28 (0.26-0.30)
Foreign body	2733	1.7	11.3	0.15 (0.13-0.16)	11681	1.9	5.5	0.08 (0.07-0.08)
Burns	1879	1.2	15.1	0.21 (0.18-0.23)	8478	1.4	9.9	0.15 (0.14-0.16)
Other and unspecified injury	14284	8.9	19.8	0.27 (0.26-0.28)	52939	8.6	13.6	0.19 (0.19-0.20)
Systemic-poisoning/toxic effects	10536	6.5	49.5	0.68 (0.67-0.70)	42280	6.9	47.5	0.64 (0.64-0.65)
Other effects of external cause/complication	1301	0.8	32.5	0.54 (0.48-0.59)	4329	0.7	27.6	0.45 (0.42-0.48)
Geographic region								
Melbourne Metropolitan Area	118959	73.7	19.8	0.28 (0.27-0.28)	227511	37.0	13.8	0.19 (0.19-0.19)
Regional/Rural Victoria	42375	26.3	19.8	0.28 (0.27-0.29)	387251	63.0	15.5	0.23 (0.23-0.23)
SEIFA state decile based on SLA[1]								
1	17503	10.8	21.6	0.31 (0.30-0.32)	65281	10.6	16.6	0.24 (0.24-0.24)
2	#	#	20.3	0.28 (0.27-0.30)	34111	5.5	14.5	0.20 (0.20-0.21)
3	10595	6.6	22.0	0.32 (0.31-0.33)	39757	6.5	15.6	0.22 (0.22-0.23)
4	17975	11.1	21.1	0.29 (0.28-0.30)	69078	11.2	16.0	0.23 (0.22-0.23)
5	10601	6.6	17.6	0.25 (0.24-0.26)	40125	6.5	13.7	0.19 (0.18-0.20)
6	11830	7.3	18.8	0.27 (0.25-0.28)	42296	6.9	13.4	0.19 (0.18-0.19)
7	11678	7.2	20.0	0.28 (0.27-0.29)	42222	6.9	13.9	0.20 (0.20-0.21)
8	25726	15.9	18.9	0.26 (0.26-0.27)	94111	15.3	14.2	0.20 (0.20-0.20)
9	23873	14.8	19.6	0.27 (0.27-0.28)	84486	13.7	15.0	0.22 (0.21-0.22)
10	22902	14.2	18.7	0.26 (0.25-0.27)	83734	13.6	15.0	0.22 (0.21-0.22)
999	<5	#	#	<5	19561	3.2	14.3	0.21 (0.20-0.22)
Country of birth								
Australia	121134	75.1	17.5	0.24 (0.24-0.24)	416571	67.8	13.0	0.18 (0.18-0.18)
New Zealand	2397	1.5	13.8	0.18 (0.16-0.20)	8016	1.3	12.4	0.16 (0.15-0.17)

England	4912	3.0	27.8	0.40 (0.38-0.42)	15077	2.5	20.0	0.29 (0.28-0.30)
Italy	3474	2.2	42.7	0.68 (0.65-0.71)	9144	1.5	29.3	0.51 (0.49-0.53)
Greece	2162	1.3	40.0	0.62 (0.58-0.66)	6201	1.0	24.0	0.39 (0.37-0.41)
India	1657	1.0	16.4	0.22 (0.19-0.24)	5949	1.0	12.4	0.17 (0.16-0.18)
All other	25598	15.9	25.0	0.36 (0.35-0.37)	153804	25.0	18.4	0.27 (0.27-0.28)

Notes:

1. SEIFA used in this study is the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD), are state deciles based on Statistical Local Areas (SLAs). A low score indicates relatively greater disadvantage. For further information refer http://www.abs.gov.au/ausstats/abs@.nsf/lookup/2033.0.55.001main+features100042011

<5 Cells with frequency less than 5 or statistics based on less than 5 patients has been suppressed for confidentiality reasons. # Other cells may also be suppressed to protect the confidentiality of <5 cells

Table E2: Characteristics of the NSW study populations

	Patients admitted[1]							
	July 2012 to June 2014, NSW (Cohort 1)				July 2008 to June 2015, NSW (Cohort 2)			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients	233521				705963			
Age group (years)								
0-14 years	31730	13.6	1.5	0.02 (0.01-0.02)	103013	14.6	1.0	0.01 (0.01-0.01)
15-24 years	33888	14.5	11.0	0.13 (0.13-0.14)	105483	14.9	7.7	0.09 (0.09-0.09)
25-44 years	51737	22.2	13.5	0.17 (0.17-0.18)	160337	22.7	9.0	0.11 (0.11-0.11)
45-64 years	44501	19.1	18.3	0.25 (0.24-0.26)	136959	19.4	11.7	0.16 (0.16-0.16)
65-84 years	44948	19.2	33.2	0.51 (0.50-0.52)	131465	18.6	22.2	0.34 (0.34-0.35)
85 and over	26717	11.4	38.2	0.60 (0.59-0.62)	68706	9.7	27.0	0.43 (0.42-0.43)
Gender								
Male[2]	131598	56.4	16.2	0.23 (0.23-0.24)	403408	57.1	10.7	0.15 (0.15-0.15)
Female	101923	43.6	22.7	0.33 (0.32-0.33)	302554	42.9	14.7	0.21 (0.21-0.21)
Injury severity[3]								
Serious injury (ICISS<0.941)	30265	13.0	35.5	0.57 (0.56-0.59)	88488	12.5	24.3	0.39 (0.38-0.39)
Other injury (ICISS>=0.941)	203256	87.0	16.6	0.23 (0.23-0.23)	617475	87.5	10.7	0.15 (0.15-0.15)
In-hospital death[4]	2295	1.0	55.4	1.14 (1.08-1.20)				
30-day mortality[5]					8240	1.2	38.4	0.71 (0.69-0.74)
1-year mortality[5]					34098	4.8	34.9	0.63 (0.61-0.64)

Notes:

1. Index admissions to all public and private hospitals, limited to residents of NSW with community injuries
2. Intersex/indeterminate patients added to the majority sex group to protect confidentiality
3. Worst injury method-ICD-based Injury Severity Score less than or equal to 0.941 considered as serious injury
4. Excludes death within 24 hours of index admission, LOS > 365 days and palliative care patients (n=232849)
5. Excludes patients who died within 24 hours of index admission (n=704041)

Table E3: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (Victoria)

Model	Outcome					
	In-hospital death[1]		30-day mortality[2]		1-year mortality[3]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
(viii) Baseline model + presence of at least one comorbidity	0.909 (0.904-0.915)	12875	0.916 (0.913-0.919)	40859	0.903 (0.901-0.905)	112229
(ix) Baseline model + count of comorbidities	0.912 (0.907-0.918)	12764	0.918 (0.915-0.921)	40726	0.904 (0.903-0.906)	111760
(x) Baseline model + individual comorbidity (all 31 conditions)	0.922 (0.917-0.927)	12434	0.924 (0.921-0.926)	39933	0.910 (0.908-0.912)	109040
(xi) Baseline model + comorbidity using actual weights	0.920 (0.915-0.925)	12446	0.923 (0.920-0.926)	39924	0.909 (0.907-0.911)	109143
Baseline model deconstructed						
Age	0.822 (0.814-0.830)	14748	0.854 (0.850-0.859)	45,417	0.871 (0.869-0.874)	119138
Age + Sex	0.834 (0.826-0.843)	14612	0.862 (0.858-0.867)	45,134	0.877 (0.875-0.879)	118590
Age + Sex + Body region			0.881 (0.877-0.885)	44,295	0.887 (0.885-0.889)	117082
Age + Sex + Body region + Injury type	0.872 (0.865-0.880)	13847	0.895 (0.891-0.899)	42,953	0.891 (0.889-0.893)	116323
Age + Sex + Body region + Injury type + Injury severity	0.894 (0.888-0.900)	13274	0.907 (0.904-0.910)	41,827	0.895 (0.893-0.897)	114942
Age + Sex + Body region + Injury type + Injury severity + SEIFA			0.908 (0.905-0.911)	41,802	0.896 (0.894-0.898)	114768
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region			0.908 (0.905-0.911)	41,768	0.896 (0.894-0.898)	114657
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region + Country of birth			0.908 (0.905-0.912)	41,745	0.896 (0.894-0.898)	114621

Notes:

1. Baseline model for in-hospital death includes age, sex, injury severity and injury type
2. Baseline model for 30-day mortality includes age, sex, injury severity, injury type, body region, socio-economic indexes for areas (SEIFA) deciles, geographic region (metropolitan Melbourne and rural Victoria) and country of birth
3. Baseline model for 1-year mortality includes age, sex, injury severity, injury type, body region, socio-economic indexes for areas (SEIFA) deciles, geographic region (metropolitan Melbourne and rural Victoria) and country of birth

Table E4: Performance of new comorbidity indices vs existing comorbidity indices using classification tables (Victoria)

Model	**In-hospital death**			
Baseline		TRUE		
	Classified	D	~D	Total
	+	1199	21377	22576
	-	365	116631	116996
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .014		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	76.66%	
	Specificity	Pr(-~D)	84.51%	
	Positive predictive value	Pr(D +)	5.31%	
	Negative predictive value	Pr(~D -)	99.69%	
	False + rate for true ~D	Pr(+~D)	15.49%	
	False - rate for true D	Pr(- D)	23.34%	
	False + rate for classified +	Pr(~D +)	94.69%	
	False - rate for classified -	Pr(D -)	0.31%	
	Correctly classified		84.42%	
Baseline + CCI		TRUE		
	Classified	D	~D	Total
	+	1292	20886	22178
	-	272	117122	117394
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .013		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	82.61%	
	Specificity	Pr(-~D)	84.87%	
	Positive predictive value	Pr(D +)	5.83%	
	Negative predictive value	Pr(~D -)	99.77%	
	False + rate for true ~D	Pr(+~D)	15.13%	
	False - rate for true D	Pr(- D)	17.39%	
	False + rate for classified +	Pr(~D +)	94.17%	
	False - rate for classified -	Pr(D -)	0.23%	

	Correctly classified		84.84%	
Baseline + Updated CCI		TRUE		
	Classified	D	~D	Total
	+	1281	19435	20716
	-	283	118573	118856
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .013		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	81.91%	
	Specificity	Pr(-~D)	85.92%	
	Positive predictive value	Pr(D +)	6.18%	
	Negative predictive value	Pr(~D -)	99.76%	
	False + rate for true ~D	Pr(+~D)	14.08%	
	False - rate for true D	Pr(- D)	18.09%	
	False + rate for classified +	Pr(~D +)	93.82%	
	False - rate for classified -	Pr(D -)	0.24%	
	Correctly classified		85.87%	
Baseline + ECM		TRUE		
	Classified	D	~D	Total
	+	1327	21042	22369
	-	237	116966	117203
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .012		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	84.85%	
	Specificity	Pr(-~D)	84.75%	
	Positive predictive value	Pr(D +)	5.93%	
	Negative predictive value	Pr(~D -)	99.80%	
	False + rate for true ~D	Pr(+~D)	15.25%	
	False - rate for true D	Pr(- D)	15.15%	
	False + rate for classified +	Pr(~D +)	94.07%	
	False - rate for classified -	Pr(D -)	0.20%	
	Correctly classified		84.75%	

Baseline + binary comorbidity index (11 conditions)		TRUE		
	Classified	D	~D	Total
	+	1317	20448	21765
	-	247	117560	117807
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .012		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	84.21%	
	Specificity	Pr(-~D)	85.18%	
	Positive predictive value	Pr(D +)	6.05%	
	Negative predictive value	Pr(~D -)	99.79%	
	False + rate for true ~D	Pr(+~D)	14.82%	
	False - rate for true D	Pr(- D)	15.79%	
	False + rate for classified +	Pr(~D +)	93.95%	
	False - rate for classified -	Pr(D -)	0.21%	
	Correctly classified		85.17%	
Baseline + comorbidity index with rounded weights (11 conditions)		TRUE		
	Classified	D	~D	Total
	+	1352	23539	24891
	-	212	114469	114681
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .011		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	86.45%	
	Specificity	Pr(-~D)	82.94%	
	Positive predictive value	Pr(D +)	5.43%	
	Negative predictive value	Pr(~D -)	99.82%	
	False + rate for true ~D	Pr(+~D)	17.06%	
	False - rate for true D	Pr(- D)	13.55%	
	False + rate for classified +	Pr(~D +)	94.57%	
	False - rate for classified -	Pr(D -)	0.18%	
	Correctly classified		82.98%	
Baseline + parsimonious comorbidity index (10 conditions)		TRUE		

	Classified	D	~D	Total
	+	1315	20416	21731
	-	249	117592	117841
	Total	1564	138008	139572
	Classified + if predicted Pr(D)	>= .012		
	True D defined as inhospmort !=	0		
	Sensitivity	Pr(+ D)	84.08%	
	Specificity	Pr(-~D)	85.21%	
	Positive predictive value	Pr(D +)	6.05%	
	Negative predictive value	Pr(~D -)	99.79%	
	False + rate for true ~D	Pr(+~D)	14.79%	
	False - rate for true D	Pr(- D)	15.92%	
	False + rate for classified +	Pr(~D +)	93.95%	
	False - rate for classified -	Pr(D -)	0.21%	
	Correctly classified		85.19%	

Table E4 continued

Model	**30-day mortality**			
Baseline		TRUE		
	Classified	D	~D	Total
	+	4111	86312	90423
	-	775	421868	422643
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .011			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	84.14%		
	Specificity Pr(-~D)	83.02%		
	Positive predictive value Pr(D +)	4.55%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	16.98%		
	False - rate for true D Pr(- D)	15.86%		
	False + rate for classified + Pr(~D +)	95.45%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	83.03%		

Baseline + CCI		TRUE		
	Classified	D	~D	Total
	+	4089	78068	82157
	-	797	430112	430909
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	83.69%		
	Specificity Pr(-~D)	84.64%		
	Positive predictive value Pr(D +)	4.98%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	15.36%		
	False - rate for true D Pr(- D)	16.31%		
	False + rate for classified + Pr(~D +)	95.02%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	84.63%		
Baseline + Updated CCI		TRUE		
	Classified	D	~D	Total
	+	4114	77201	81315
	-	772	430979	431751
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	84.20%		
	Specificity Pr(-~D)	84.81%		
	Positive predictive value Pr(D +)	5.06%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	15.19%		
	False - rate for true D Pr(- D)	15.80%		
	False + rate for classified + Pr(~D +)	94.94%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	84.80%		
Baseline + ECM		TRUE		
	Classified	D	~D	Total

	+	4163	77142	81305
	-	723	431038	431761
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	85.20%		
	Specificity Pr(-~D)	84.82%		
	Positive predictive value Pr(D +)	5.12%		
	Negative predictive value Pr(~D -)	99.83%		
	False + rate for true ~D Pr(+~D)	15.18%		
	False - rate for true D Pr(- D)	14.80%		
	False + rate for classified + Pr(~D +)	94.88%		
	False - rate for classified - Pr(D -)	0.17%		
	Correctly classified	84.82%		
Baseline + binary comorbidity index (13 conditions)		TRUE		
	Classified	D	~D	Total
	+	4116	75721	79837
	-	770	432459	433229
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	84.24%		
	Specificity Pr(-~D)	85.10%		
	Positive predictive value Pr(D +)	5.16%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	14.90%		
	False - rate for true D Pr(- D)	15.76%		
	False + rate for classified + Pr(~D +)	94.84%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	85.09%		
Baseline + comorbidity index with rounded weights (13 conditions)		TRUE		
	Classified	D	~D	Total
	+	4125	76099	80224

	-	761	432081	432842
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	84.42%		
	Specificity Pr(-~D)	85.03%		
	Positive predictive value Pr(D +)	5.14%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	14.97%		
	False - rate for true D Pr(- D)	15.58%		
	False + rate for classified + Pr(~D +)	94.86%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	85.02%		
Baseline + parsimonious comorbidity index (10 conditions)		TRUE		
	Classified	D	~D	Total
	+	4105	76108	80213
	-	781	432072	432853
	Total	4886	508180	513066
	Classified + if predicted Pr(D) >= .012			
	True D defined as onemnthmort != 0			
	Sensitivity Pr(+ D)	84.02%		
	Specificity Pr(-~D)	85.02%		
	Positive predictive value Pr(D +)	5.12%		
	Negative predictive value Pr(~D -)	99.82%		
	False + rate for true ~D Pr(+~D)	14.98%		
	False - rate for true D Pr(- D)	15.98%		
	False + rate for classified + Pr(~D +)	94.88%		
	False - rate for classified - Pr(D -)	0.18%		
	Correctly classified	85.01%		

Table E4 continued

Model	**1-year mortality**			
Baseline		TRUE		
	Classified	D	~D	Total

	+	15247	86602	101849
	-	3228	409059	412287
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .052			
	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	82.53%		
	Specificity Pr(-~D)	82.53%		
	Positive predictive value Pr(D +)	14.97%		
	Negative predictive value Pr(~D -)	99.22%		
	False + rate for true ~D Pr(+~D)	17.47%		
	False - rate for true D Pr(- D)	17.47%		
	False + rate for classified + Pr(~D +)	85.03%		
	False - rate for classified - Pr(D -)	0.78%		
	Correctly classified	82.53%		
Baseline + CCI		TRUE		
	Classified	D	~D	Total
	+	15436	82306	97742
	-	3039	413355	416394
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .05			
	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	83.55%		
	Specificity Pr(-~D)	83.39%		
	Positive predictive value Pr(D +)	15.79%		
	Negative predictive value Pr(~D -)	99.27%		
	False + rate for true ~D Pr(+~D)	16.61%		
	False - rate for true D Pr(- D)	16.45%		
	False + rate for classified + Pr(~D +)	84.21%		
	False - rate for classified - Pr(D -)	0.73%		
	Correctly classified	83.40%		
Baseline + Updated CCI		TRUE		
	Classified	D	~D	Total
	+	15230	76869	92099
	-	3245	418792	422037

	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .055			
	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	82.44%		
	Specificity Pr(-~D)	84.49%		
	Positive predictive value Pr(D +)	16.54%		
	Negative predictive value Pr(~D -)	99.23%		
	False + rate for true ~D Pr(+~D)	15.51%		
	False - rate for true D Pr(- D)	17.56%		
	False + rate for classified + Pr(~D +)	83.46%		
	False - rate for classified - Pr(D -)	0.77%		
	Correctly classified	84.42%		
Baseline + ECM		TRUE		
	Classified	D	~D	Total
	+	15457	81153	96610
	-	3018	414508	417526
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .051			
	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	83.66%		
	Specificity Pr(-~D)	83.63%		
	Positive predictive value Pr(D +)	16.00%		
	Negative predictive value Pr(~D -)	99.28%		
	False + rate for true ~D Pr(+~D)	16.37%		
	False - rate for true D Pr(- D)	16.34%		
	False + rate for classified + Pr(~D +)	84.00%		
	False - rate for classified - Pr(D -)	0.72%		
	Correctly classified	83.63%		
Baseline + binary comorbidity index (19 conditions)		TRUE		
	Classified	D	~D	Total
	+	15464	80151	95615
	-	3011	415510	418521
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .051			

	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	83.70%		
	Specificity Pr(-~D)	83.83%		
	Positive predictive value Pr(D +)	16.17%		
	Negative predictive value Pr(~D -)	99.28%		
	False + rate for true ~D Pr(+~D)	16.17%		
	False - rate for true D Pr(- D)	16.30%		
	False + rate for classified + Pr(~D +)	83.83%		
	False - rate for classified - Pr(D -)	0.72%		
	Correctly classified	83.82%		
Baseline + comorbidity index with rounded weights (17 conditions)		TRUE		
	Classified	D	~D	Total
	+	15461	80301	95762
	-	3014	415360	418374
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .051			
	True D defined as oneyrmort != 0			
	Sensitivity Pr(+ D)	83.69%		
	Specificity Pr(-~D)	83.80%		
	Positive predictive value Pr(D +)	16.15%		
	Negative predictive value Pr(~D -)	99.28%		
	False + rate for true ~D Pr(+~D)	16.20%		
	False - rate for true D Pr(- D)	16.31%		
	False + rate for classified + Pr(~D +)	83.85%		
	False - rate for classified - Pr(D -)	0.72%		
	Correctly classified	83.80%		
Baseline + parsimonious comorbidity index (10 conditions)		TRUE		
	Classified	D	~D	Total
	+	15448	80577	96025
	-	3027	415084	418111
	Total	18475	495661	514136
	Classified + if predicted Pr(D) >= .051			
	True D defined as oneyrmort != 0			

	Sensitivity Pr(+ D)	83.62%		
	Specificity Pr(-~D)	83.74%		
	Positive predictive value Pr(D +)	16.09%		
	Negative predictive value Pr(~D -)	99.28%		
	False + rate for true ~D Pr(+~D)	16.26%		
	False - rate for true D Pr(- D)	16.38%		
	False + rate for classified + Pr(~D +)	83.91%		
	False - rate for classified - Pr(D -)	0.72%		
	Correctly classified	83.74%		

Table E5: Performance of new comorbidity indices vs existing comorbidity indices in injury sub-groups (Victoria)

Model	Children (<15 years)		Adults (>=65 years)	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
	In-hospital death[1]			
Baseline model	0.640 (0.380-0.901)	76	0.751 (0.738-0.764)	11630
Baseline model + individual comorbidity (11 conditions) (binary representation)	0.835 (0.686-0.985)	59	0.820 (0.809-0.831)	10870
Baseline model + comorbidity using CCI weights	0.641 (0.379-0.904)	77	0.802 (0.790-0.813)	11129
Baseline model + comorbidity using ECM	0.834 (0.680-0.988)	60	0.819 (0.808-0.830)	10887
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.835 (0.686-0.985)	59	0.820 (0.809-0.831)	10884
Baseline model + individual comorbidity (9 conditions created for the >65 years)			0.819 (0.808-0.830)	10882
Baseline model + individual comorbidity (8 conditions common to all three outcomes created for the >65 years)			0.819 (0.808-0.830)	10896
	30-day mortality[2]			
Baseline model	0.917 (0.852-0.981)	314	0.724 (0.716-0.732)	35604
Baseline model + individual comorbidity (13 conditions) (binary representation)	0.966 (0.939-0.992)	255	0.781 (0.774-0.788)	33746
Baseline model + comorbidity using CCI weights	0.942 (0.895-0.989)	307	0.761 (0.753-0.768)	34550
Baseline model + comorbidity using ECM	0.966 (0.940-0.991)	251	0.769 (0.762-0.777)	34248
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.962 (0.935-0.989)	257	0.779 (0.772-0.786)	33785
Baseline model + individual comorbidity (12 conditions created for the >65 years)			0.780 (0.773-0.788)	33741
Baseline model + individual comorbidity (8 conditions common to all three outcomes created for the >65 years)			0.778 (0.771-0.785)	33823
	1-year mortality[3]			
Baseline model	0.867 (0.807-0.927)	722	0.655 (0.651-0.660)	97546
Baseline model + individual comorbidity (19 conditions) (binary representation)	0.882 (0.823-0.940)	674	0.716 (0.712-0.720)	92141
Baseline model + comorbidity using CCI weights	0.872 (0.811-0.933)	714	0.695 (0.690-0.699)	94370
Baseline model + comorbidity using ECM	0.882 (0.823-0.942)	658	0.701 (0.697-0.706)	93615
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.876 (0.817-0.935)	679	0.714 (0.710-0.719)	92224

Baseline model + individual comorbidity (15 conditions created for the >65 years)			0.717 (0.713-0.721)	92052
Baseline model + individual comorbidity (8 conditions common to all three outcomes created for the >65 years)			0.714 (0.710-0.718)	92270

Table E5 continued

Model	Non-severe injury (adults)		Intracranial injury[4] (adults)	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
	In-hospital death[1]			
Baseline model	0.865 (0.853-0.876)	5662	0.843 (0.825-0.861)	1591
Baseline model + individual comorbidity (11 conditions) (binary representation)	0.911 (0.900-0.922)	5084	0.861 (0.843-0.879)	1561
Baseline model + comorbidity using CCI weights	0.903 (0.892-0.914)	5216	0.856 (0.837-0.874)	1558
Baseline model + comorbidity using ECM	0.920 (0.911-0.929)	5060	0.867 (0.850-0.885)	1558
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.911 (0.900-0.922)	5085	0.861 (0.843-0.879)	1561
	30-day mortality[2]			
Baseline model	0.897 (0.891-0.902)	20430	0.877 (0.868-0.886)	4722
Baseline model + individual comorbidity (13 conditions) (binary representation)	0.917 (0.911-0.922)	19359	0.890 (0.881-0.899)	4591
Baseline model + comorbidity using CCI weights	0.912 (0.906-0.917)	19632	0.885 (0.876-0.894)	4638
Baseline model + comorbidity using ECM	0.918 (0.913-0.923)	19407	0.892 (0.883-0.901)	4601
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.915 (0.910-0.920)	19415	0.889 (0.880-0.898)	4590
	1-year mortality[3]			
Baseline model	0.899 (0.896-0.902)	74776	0.874 (0.866-0.882)	7149
Baseline model + individual comorbidity (19 conditions) (binary representation)	0.911 (0.909-0.914)	71266	0.889 (0.881-0.897)	6864
Baseline model + comorbidity using CCI weights	0.908 (0.906-0.911)	72307	0.884 (0.876-0.892)	6970
Baseline model + comorbidity using ECM	0.911 (0.909-0.913)	71584	0.888 (0.881-0.896)	6936
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.910 (0.908-0.913)	71514	0.888 (0.880-0.895)	6875

Table E5 continued

Model	Hip-fracture[5]	Blunt trauma[6]

	AUC (95% CI)	Model	AUC (95% CI)	Model fit
	In-hospital death[1]			
Baseline model	0.578 (0.556-0.600)	3804	0.876 (0.869-0.883)	11557
Baseline model + individual comorbidity (11 conditions) (binary representation)	0.697 (0.673-0.721)	3582	0.908 (0.901-0.914)	10825
Baseline model + comorbidity using CCI weights	0.657 (0.633-0.681)	3692	0.902 (0.895-0.908)	11008
Baseline model + comorbidity using ECM	0.696 (0.671-0.721)	3582	0.909 (0.903-0.915)	10791
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.692 (0.668-0.716)	3599	0.907 (0.901-0.913)	10845
	30-day mortality[2]			
Baseline model	0.595 (0.580-0.610)	11019	0.897 (0.893-0.900)	35176
Baseline model + individual comorbidity (13 conditions) (binary representation)	0.712 (0.699-0.726)	10377	0.914 (0.911-0.917)	33642
Baseline model + comorbidity using CCI weights	0.664 (0.650-0.678)	10764	0.909 (0.906-0.912)	34166
Baseline model + comorbidity using ECM	0.679 (0.664-0.693)	10651	0.911 (0.908-0.915)	33981
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.712 (0.698-0.726)	10374	0.913 (0.910-0.917)	33681
	1-year mortality[3]			
Baseline model	0.581 (0.571-0.590)	22587	0.885 (0.883-0.887)	94843
Baseline model + individual comorbidity (19 conditions) (binary representation)	0.700 (0.692-0.709)	20888	0.901 (0.899-0.903)	90201
Baseline model + comorbidity using CCI weights	0.661 (0.652-0.670)	21735	0.896 (0.894-0.898)	91654
Baseline model + comorbidity using ECM	0.663 (0.654-0.672)	21566	0.898 (0.896-0.900)	91192
Baseline model + comorbidity common to all three outcomes (10 conditions)	0.699 (0.690-0.707)	20890	0.900 (0.898-0.902)	90350

Notes:

1. Baseline model for in-hospital death includes age, sex, injury severity and injury type
2. Baseline model for 30-day mortality includes age, sex, injury severity, injury type, body region, socio-economic indexes for areas (SEIFA) deciles, geographic region (metropolitan Melbourne and rural Victoria) and country of birth
3. Baseline model for 1-year mortality includes age, sex, injury severity, injury type, body region and SEIFA deciles
4. Intracranial injury = ICD-10-AM codes S0600 - S0699
5. Hip fractures = ICD-10 codes S72.0 - S72.2
6. Blunt trauma = ICD-10 codes V00-V99, W00-W19, W20-W24, W30-W31, W50-W52, X50, X79-X82, Y00-Y05, Y29-Y32 and Y85

Table E6: Presence of comorbidity and the proportion of patients with mortality outcome in the NSW study population (age >= 15 years)

Comorbidity	In-hospital death[1]		Cohort 2 (N=601136) n (%)	30-day mortality[2]	1-year mortality[2]
	Cohort 1 (N=201151) n (%)	% with condition that had the outcome		% with condition that had the outcome	% with condition that had the outcome
HIV/AIDS	48 (0.0)	*	89 (0.0)	*	7.9
Alcohol dependence	10952 (5.4)	0.5	22976 (3.8)	0.7	3.2
Drug dependence	3101 (1.5)	0.4	5627 (0.9)	0.6	3.0
Any malignancy	821 (0.4)	20.8	1895 (0.3)	22.7	69.1
Blood loss anaemia	151 (0.1)	3.3	323 (0.1)	3.1	20.1
Cardiac arrhythmias	5542 (2.8)	6.1	11782 (2.0)	6.0	21.7
Cerebrovascular disease	1071 (0.5)	7.0	2343 (0.4)	7.7	22.9
Chronic pulmonary disease	1661 (0.8)	7.6	3414 (0.6)	8.3	27.8
Coagulopathy	1202 (0.6)	7.7	2350 (0.4)	7.9	24.6
Congestive heart failure	1386 (0.7)	16.2	2914 (0.5)	16.2	45.1
Deficiency anaemias	681 (0.3)	3.4	1360 (0.2)	3.7	24.2
Dementia	5667 (2.8)	4.8	11337 (1.9)	8.8	34.4
Depression	5706 (2.8)	0.5	11969 (2.0)	0.8	3.5
Diabetes with chronic complications	4441 (2.2)	4.4	7810 (1.3)	4.3	18.9
Diabetes without complications	10683 (5.3)	1.9	15387 (2.6)	2.2	11.4
Hemiplegia/paraplegia	950 (0.5)	6.1	1999 (0.3)	6.2	18.4
Hypertension complicated	44 (0.0)	11.4	105 (0.0)	9.5	27.6
Hypertension uncomplicated	7022 (3.5)	5.1	15069 (2.5)	4.9	18.4
Hypothyroidism	309 (0.2)	2.3	613 (0.1)	3.1	15.2
Metastatic solid tumor	458 (0.2)	26.6	1046 (0.2)	27.7	79.9
Mild liver disease	1342 (0.7)	2.2	2212 (0.4)	2.6	12.3
Moderate or severe liver disease	156 (0.1)	10.9	292 (0.0)	16.4	39.7
Myocardial infarction	444 (0.2)	14.2	1098 (0.2)	15.2	33.3
Obesity	500 (0.2)	1.8	994 (0.2)	1.9	8.2
Peptic ulcer disease	104 (0.1)	6.7	222 (0.0)	2.3	16.7
Peripheral vascular disease	446 (0.2)	5.6	1076 (0.2)	5.4	21.7
Psychoses	929 (0.5)	0.6	1883 (0.3)	0.7	5.1

Pulmonary circulation disorders	341 (0.2)	15.5	725 (0.1)	13.1	36.7
Renal disease including renal failure	3432 (1.7)	8.6	6195 (1.0)	9.0	31.9
Rheumatic disease including some other connective tissue disorders	307 (0.2)	4.6	647 (0.1)	1.7	11.9
Valvular disease	546 (0.3)	8.4	1122 (0.2)	9.6	29.9

1. Excludes death within 24 hours of index admission, LOS > 365 days and palliative care patients
2. Excludes patients who died within 24 hours of index admission
* Cell count 1-4 suppressed to protect confidentiality

Table E7: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (NSW, age >= 15 years)

	In-hospital death[1]		30-day mortality[2]		1-year mortality[3]	
Model	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC	Model fit AIC
Baseline model	0.891 (0.886-0.896)	19542	0.886 (0.884-0.889)	67661	0.880 (0.879-0.882)	191035
Baseline model + (AICI-hd/AICI-30d/AICI-1yr)	0.914 (0.910-0.918)	18441	0.901 (0.898-0.903)	65366	0.893 (0.891-0.894)	183403
Baseline model + comorbidity using CCI weights	0.908 (0.904-0.913)	18759	0.896 (0.894-0.899)	67661	0.889 (0.888-0.890)	185895
Baseline model + comorbidity using ECM	0.917 (0.913-0.921)	18334	0.901 (0.898-0.903)	65454	0.891 (0.890-0.893)	184157
Baseline model + AICI-m	0.914 (0.909-0.918)	18442	0.900 (0.897-0.902)	65470	0.892 (0.891-0.893)	183662

1. Baseline model for in-hospital death includes age, sex, injury severity and injury type
2. Baseline model for 30-day mortality includes age, sex, injury severity, injury type, body region, socio-economic indexes for areas (SEIFA) deciles, geographic region (metropolitan NSW and rural NSW) and country of birth
3. Baseline model for 1-year mortality includes age, sex, injury severity, injury type, body region, socio-economic indexes for areas (SEIFA) deciles, geographic region (metropolitan Melbourne and rural Victoria) and country of birth
Note: See Table 5 for selected comorbidities for each outcome

Table E8: Conditions included in the Australian Injury Comorbidity Indices for mortality, CCI and ECM

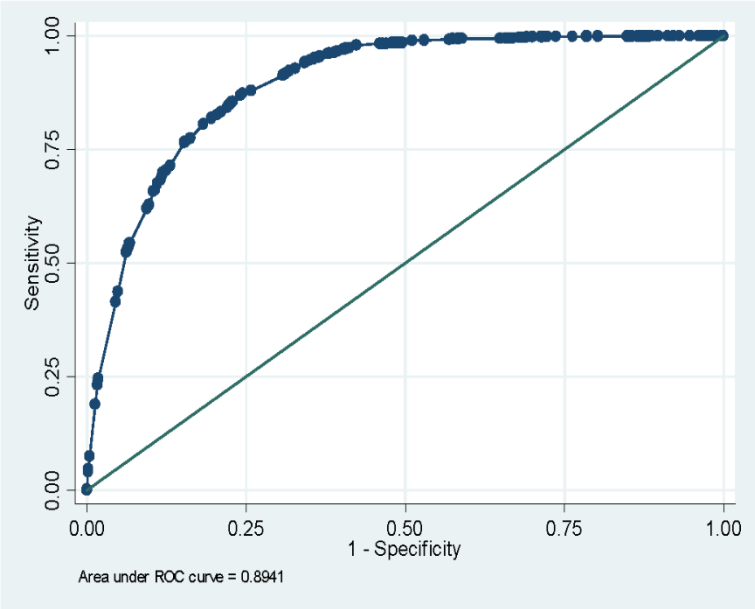
Comorbidity	Outcome					
	In-hospital death (AICI-hd)[1]	30-day mortality (AICI-30d)[2]	1-year mortality (AICI-1yr)[3]	Mortality (AICI-m)[4]	1-year mortality (CCI)	In-hospital death (ECM)
HIV/AIDS	X	X	X	X	✓	✓
Alcohol dependence	X	X	X	X	X	✓
Drug dependence	X	X	✓	X	X	✓
Any malignancy	✓[5]	✓[5]	✓[5]	✓[5]	✓[5]	✓[6]
Blood loss anaemia	X	X	X	X	X	✓
Cardiac arrhythmias	✓	✓	✓	✓	X	✓
Cerebrovascular disease	X	✓	X	X	✓	X
Chronic pulmonary disease	✓	✓	✓	✓	✓	✓
Coagulopathy	✓	✓	✓	✓	X	✓
Congestive heart failure	✓	✓	✓	✓	✓	✓
Deficiency anaemias	X	X	✓	X	X	✓
Dementia	✓	✓	✓	✓	✓	X
Depression	X	X	X	X	X	✓
Diabetes with chronic complications	X	X	✓	X	✓	✓
Diabetes without complications	X	X	✓	X	✓	✓
Fluid and electrolyte disorders	X	X	X	X	X	✓
Hemiplegia/paraplegia	X	X	✓	X	✓	✓
Hypertension complicated	X	X	X	X	X	✓
Hypertension uncomplicated	X	X	X	X	X	✓
Hypothyroidism	X	X	X	X	X	✓
Metastatic solid tumor	✓	✓	✓	✓	✓	✓
Mild liver disease	✓	✓	✓	✓	✓	✓
Moderate or severe liver disease	X	✓	✓	X	✓	
Myocardial infarction	✓	✓	✓	✓	✓	X
Obesity	X	X	X	X	X	✓

Other neurological disorders	X	X	X	X	X	✓
Peptic ulcer disease	✓	X	X	X	✓	✓
Peripheral vascular disease	X	✓	✓	X	✓	✓
Psychoses	X	X	✓	X	X	✓
Pulmonary circulation disorders	X	X	✓	X	X	✓
Renal disease including renal failure	✓	✓	✓	✓	✓	✓
Rheumatic disease including some other connective tissue disorders	X	X	X	X	✓	✓
Valvular disease	X	X	X	X	X	✓
Weight loss	X	X	X	X	X	✓

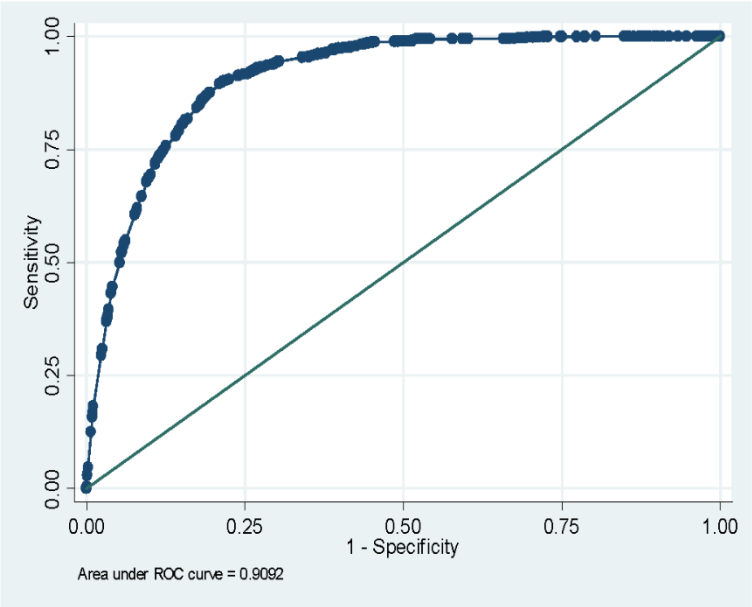
Notes:
1. AICI-hd - Injury Comorbidity Index - in-hospital death
2. AICI-30d - Injury Comorbidity Index - 30-day mortality
3. AICI-1yr - Injury Comorbidity Index - 1-year mortality
4. AICI-m - Injury Comorbidity Index - mortality
5. Includes lymphoma, solid tumors without metastasis and leukaemia
6. Includes lymphoma and solid tumors without metastasis

Appendix E1.1 – ROC curves for in-hospital death (age >= 15 years)

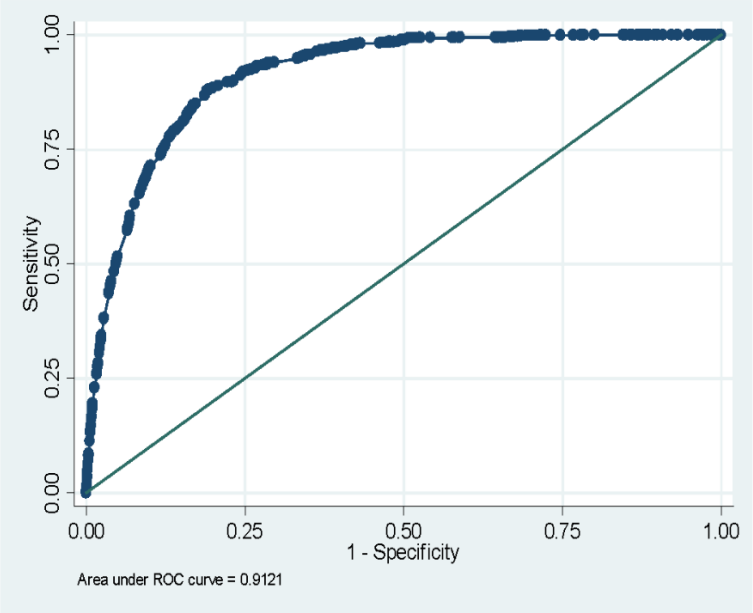
Baseline model (age, sex, injury-severity and injury-type)



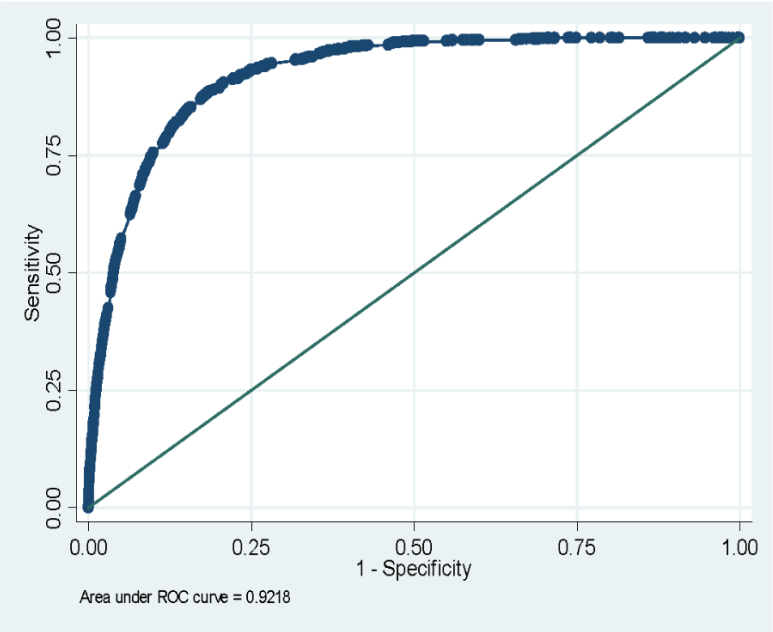
Baseline model (age, sex, injury-severity and injury-type) + at least one comorbidity



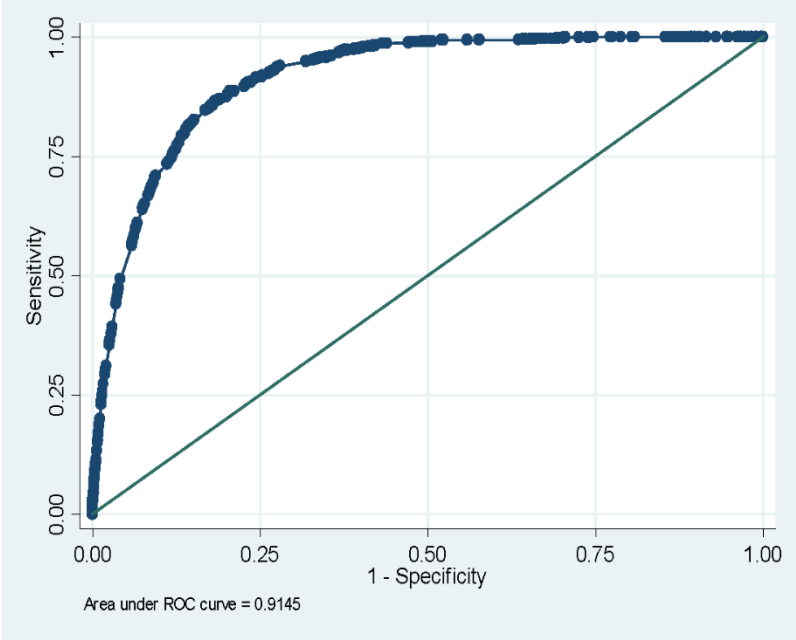
Baseline model (age, sex, injury-severity and injury-type) + count of comorbidities



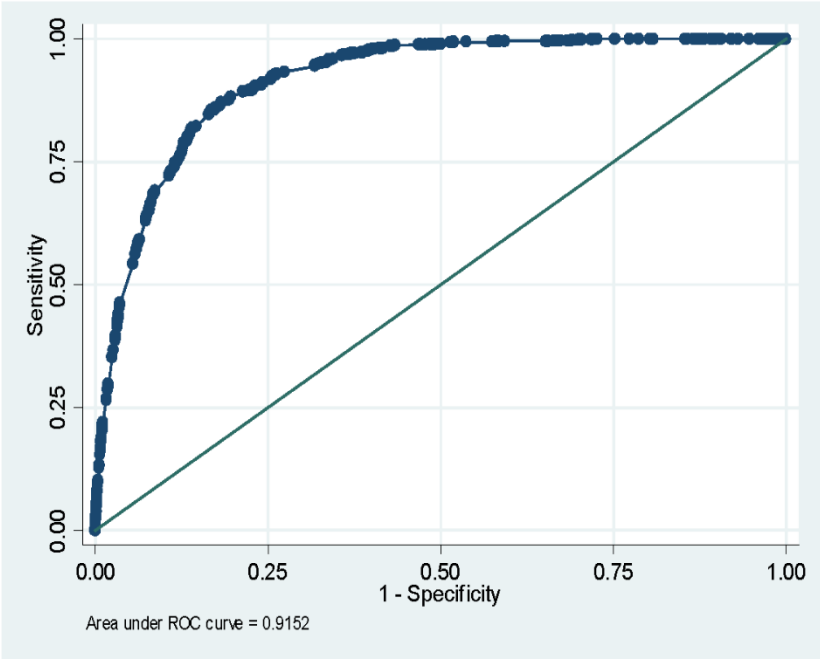
Baseline model (age, sex, injury-severity and injury-type) + all 31 comorbidities added as binary variables at the same time



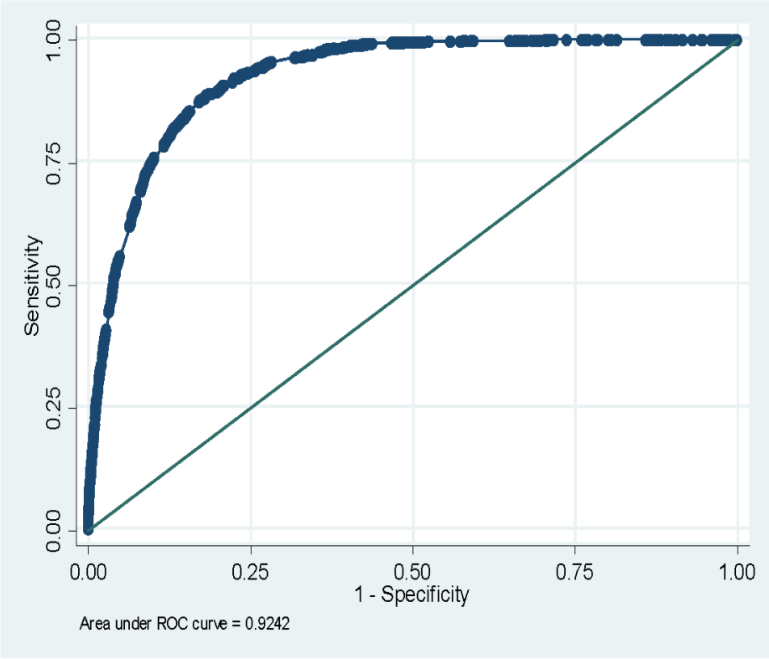
Baseline model (age, sex, injury-severity and injury-type) + Charlson Comorbidity Index (CCI)



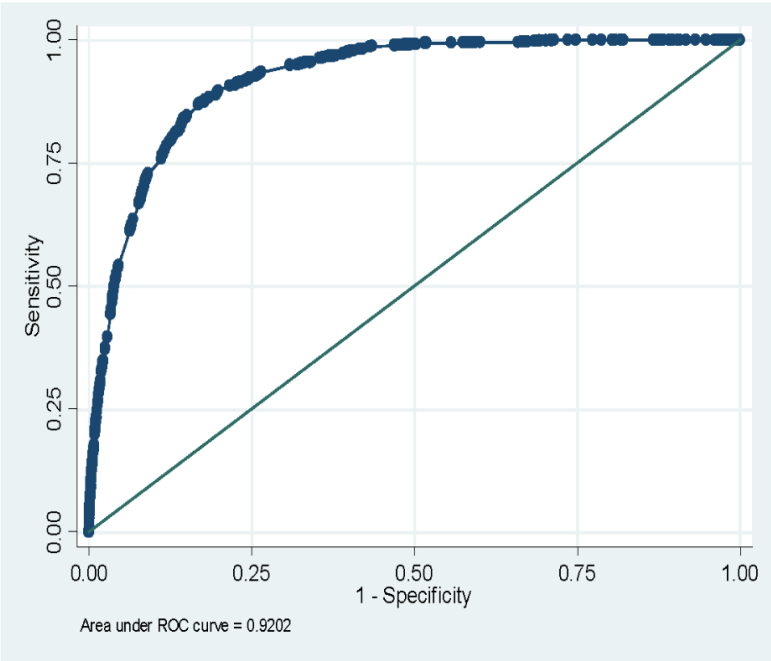
Baseline model (age, sex, injury-severity and injury-type) + CCI updated by Quan et al. 2005



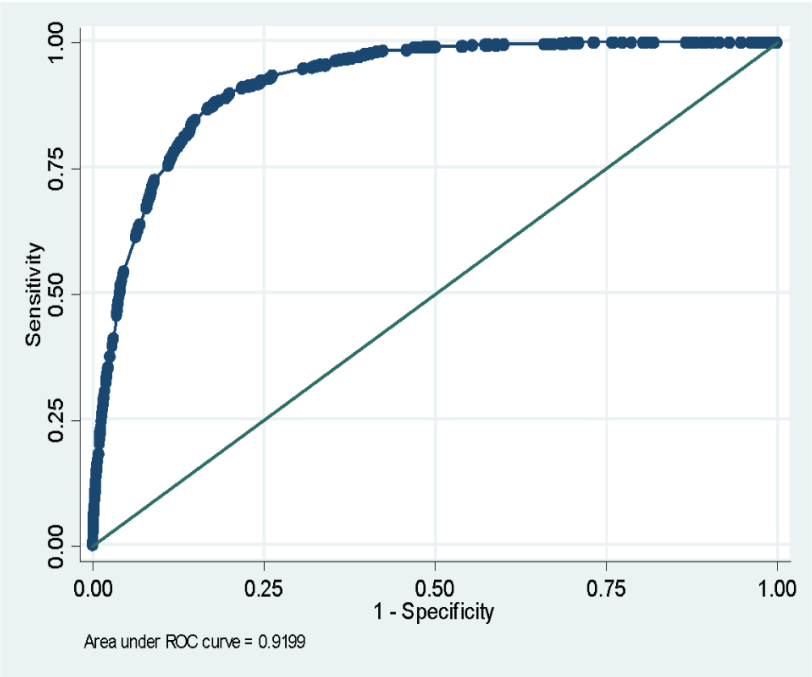
Baseline model (age, sex, injury-severity and injury-type) + Elixhauser Comorbidity Measure (ECM)



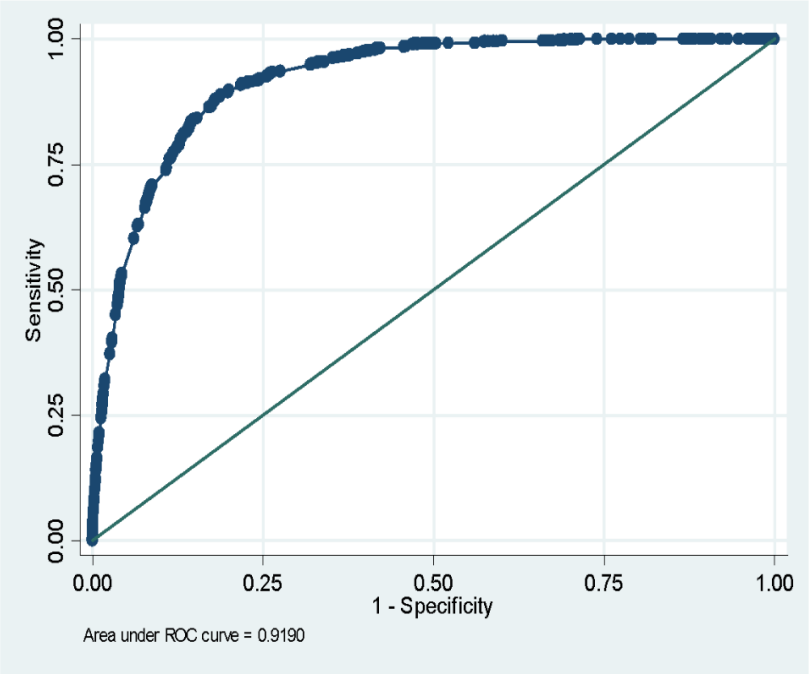
Baseline model (age, sex, injury-severity and injury-type) + AICI-hd (binary comorbidity index with 11 conditions)



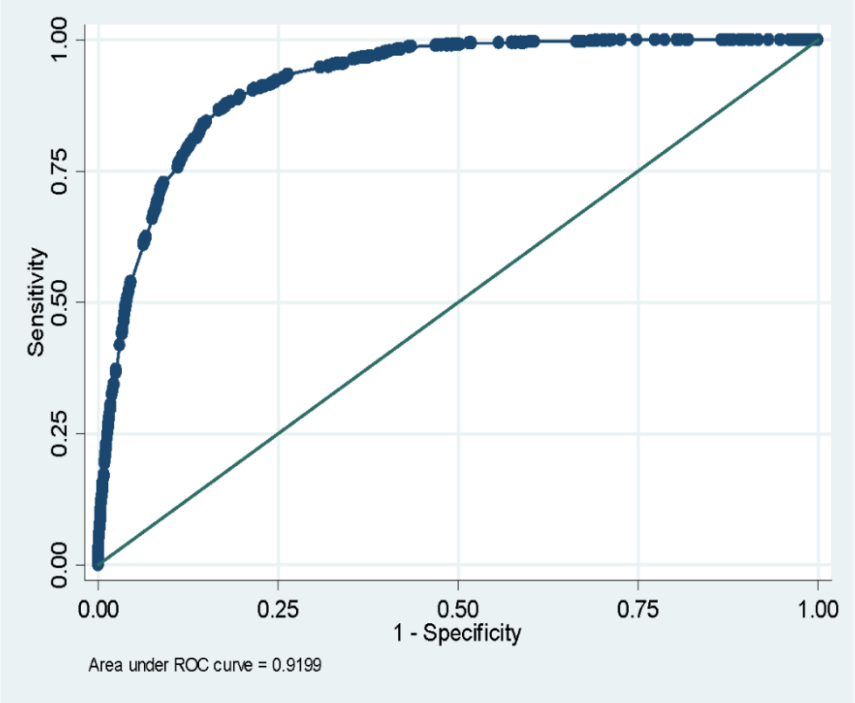
Baseline model (age, sex, injury-severity and injury-type) + comorbidity index with actual weights (11 conditions)



Baseline model (age, sex, injury-severity and injury-type) + comorbidity index with rounded weights (11 conditions)

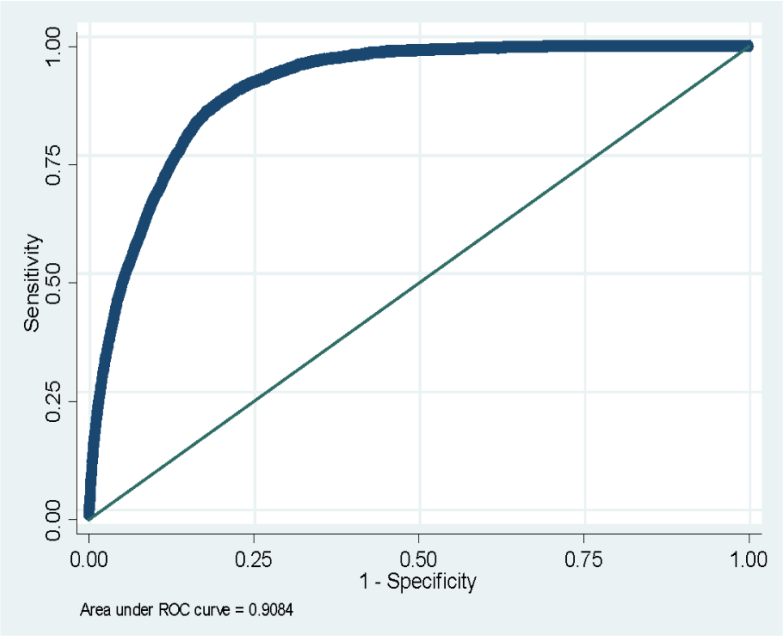


Baseline model (age, sex, injury-severity and injury-type) + AICI-m (parsimonious comorbidity index with 10 conditions)

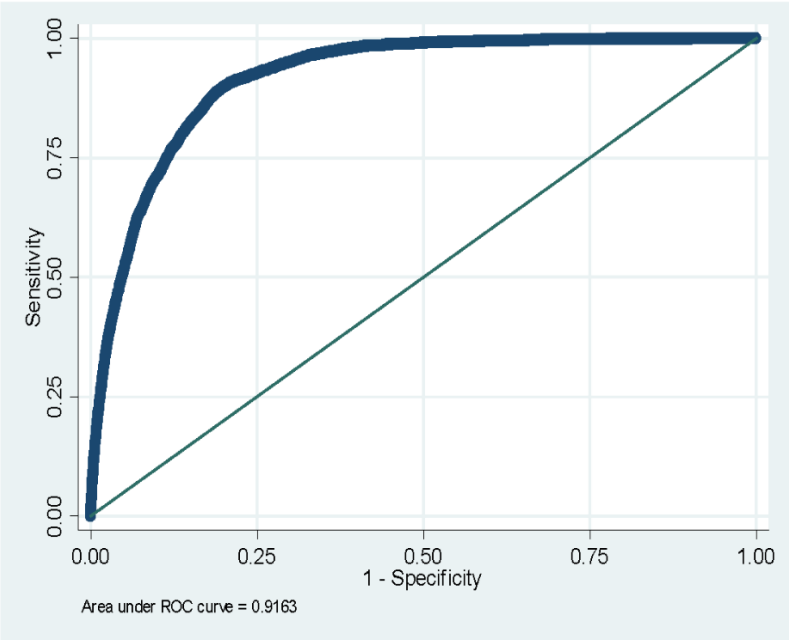


Appendix E1.2 - ROC curves for 30-day mortality (age >=15 years)

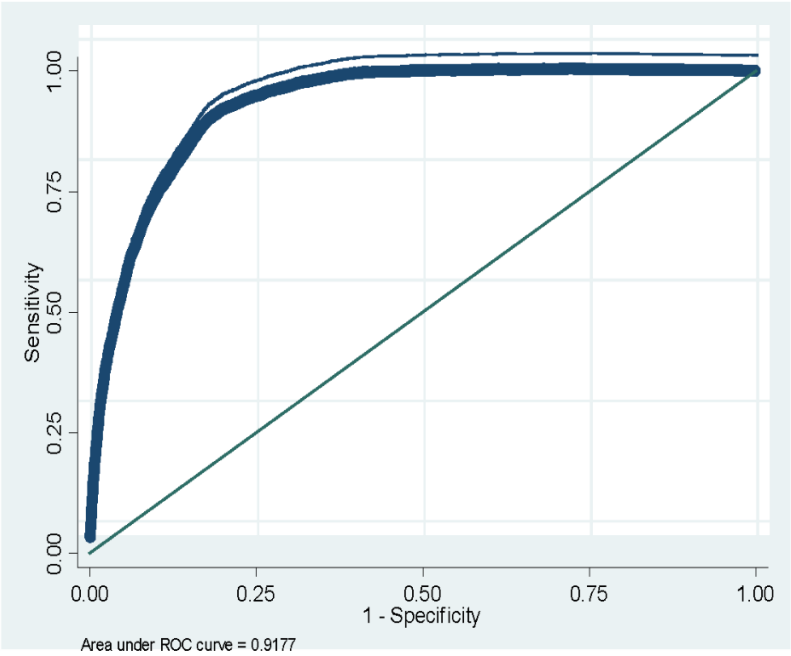
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth)



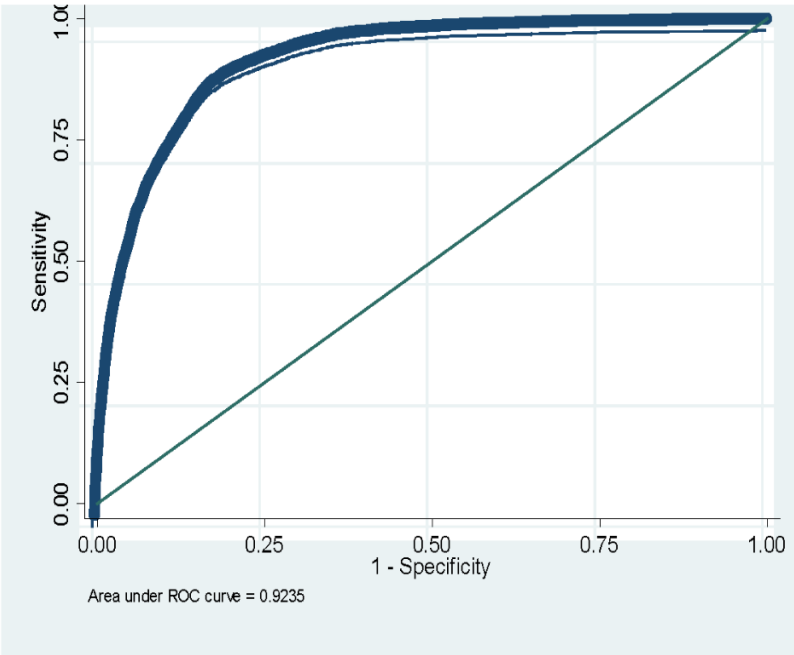
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + at least one comorbidity



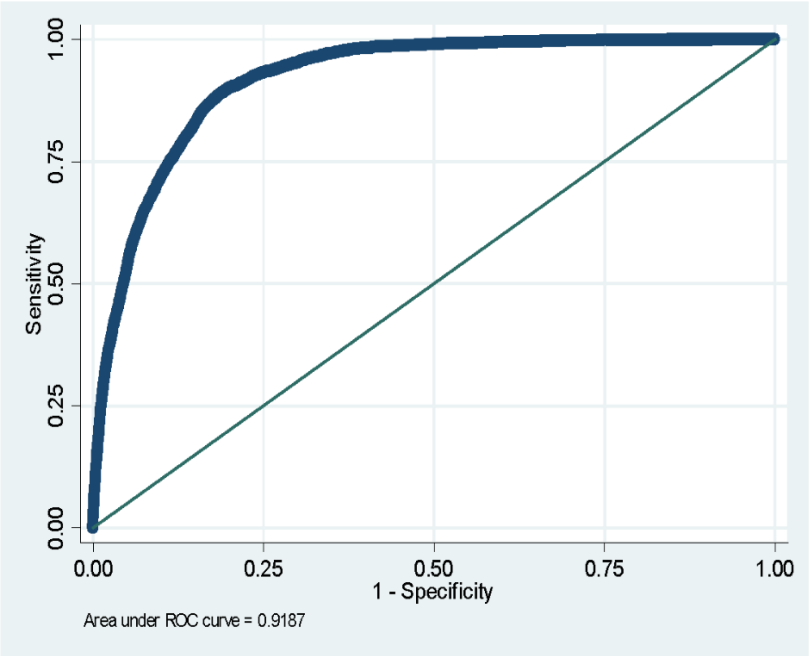
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + count of comorbidities



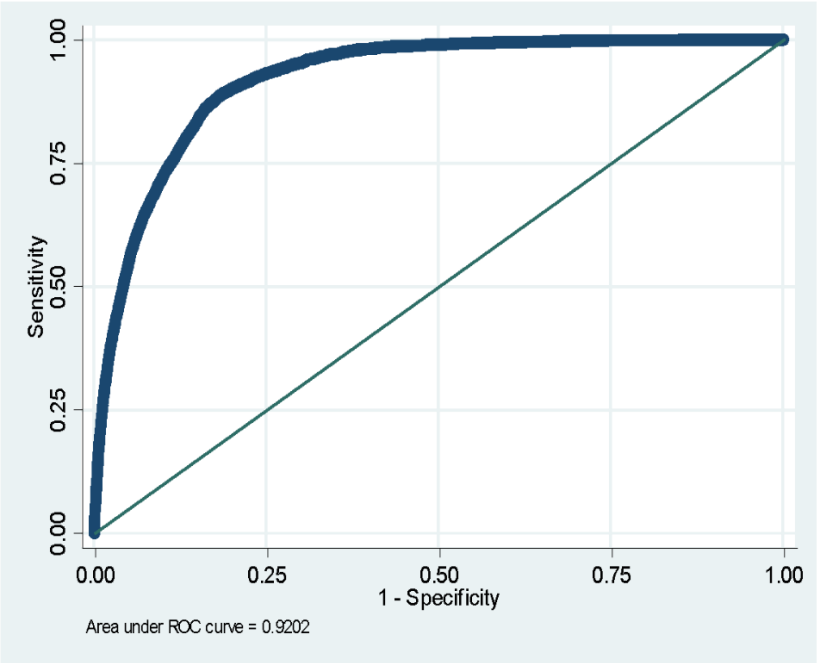
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + all 31 comorbidities added as binary variables at the same time



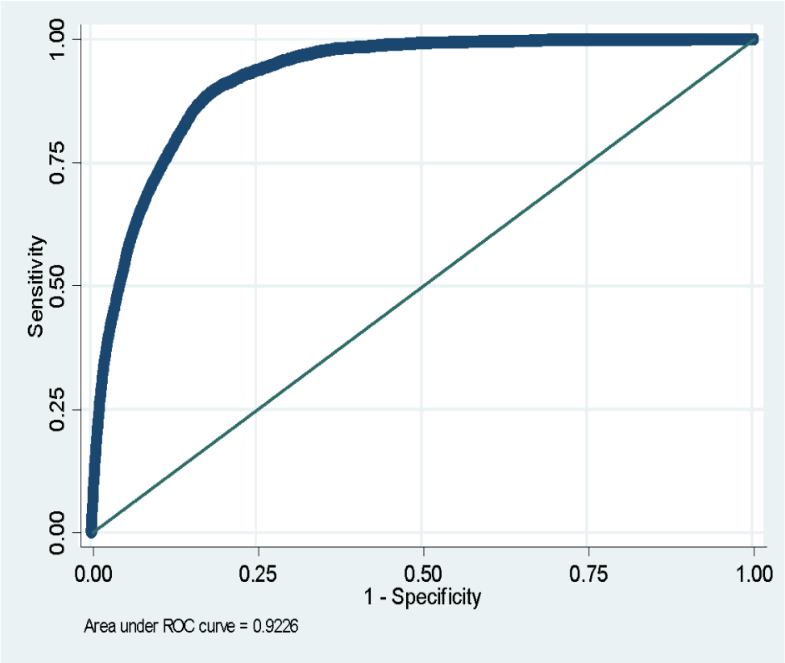
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + Charlson Comorbidity Index (CCI)



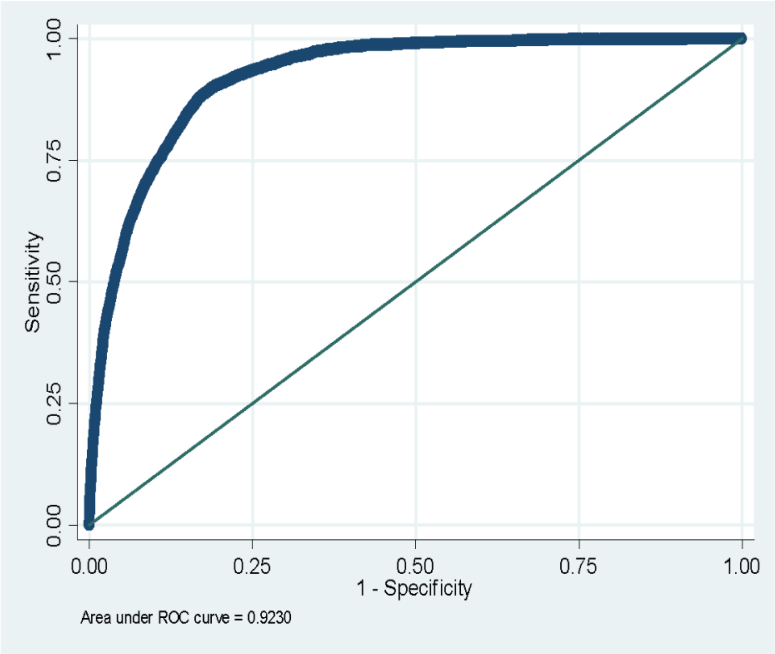
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + CCI updated by Quan et al. 2005



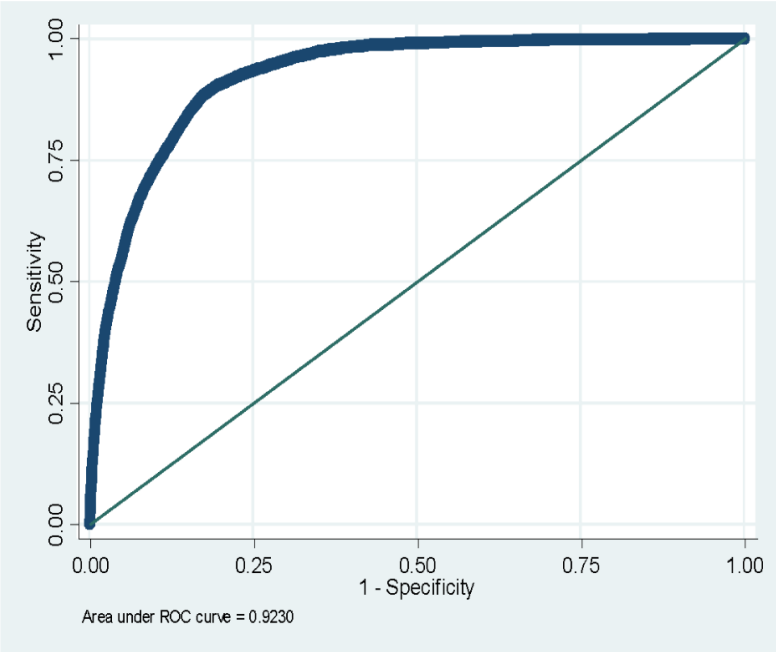
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + Elixhauser Comorbidity Measure (ECM)



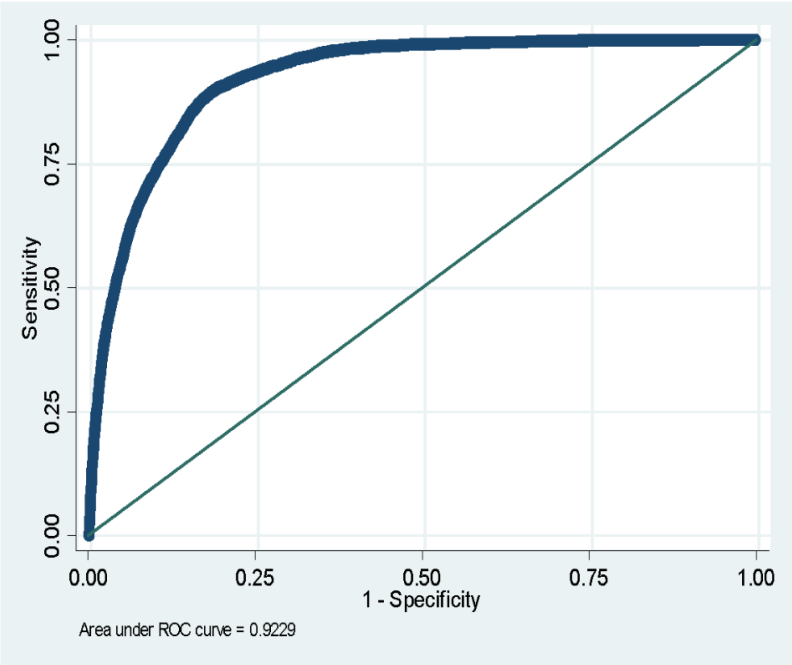
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + AICI-30d (binary comorbidity index with 13 conditions)



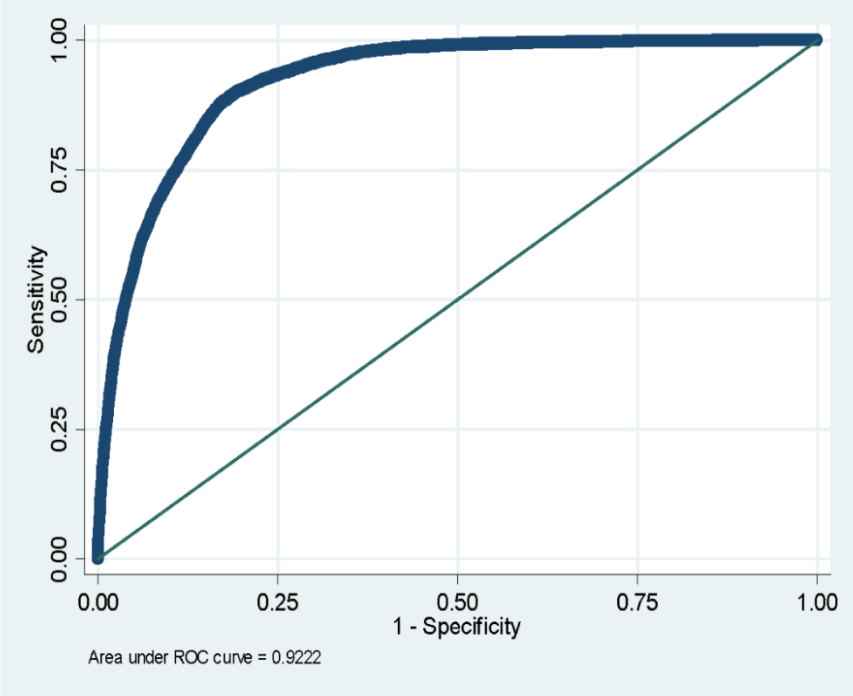
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + comorbidity index with actual weights (13 conditions)



Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + comorbidity index with rounded weights (13 conditions)

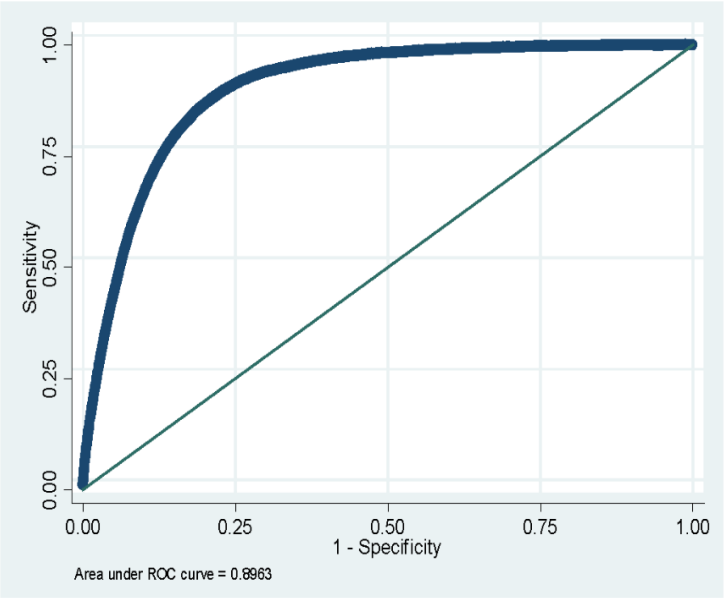


Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + AICI-m (parsimonious comorbidity index with 10 conditions)

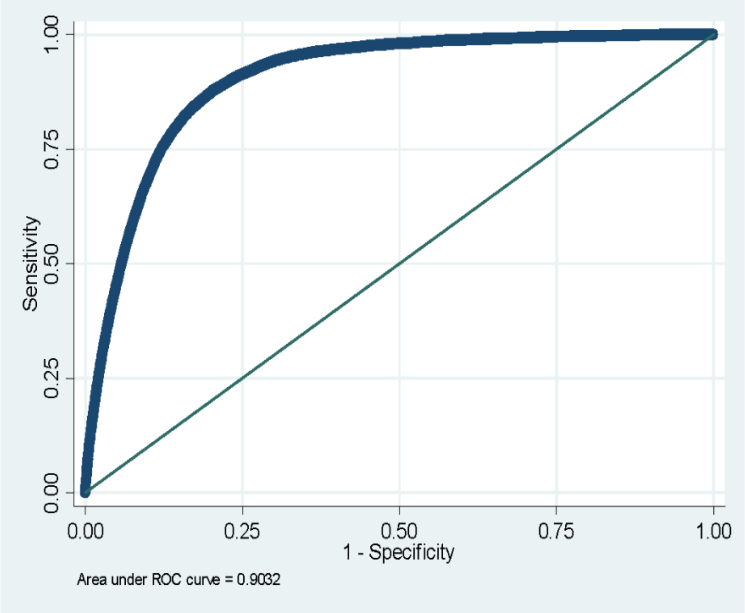


Appendix E1.3 – ROC curves for 1-year mortality (age >= 15 years)

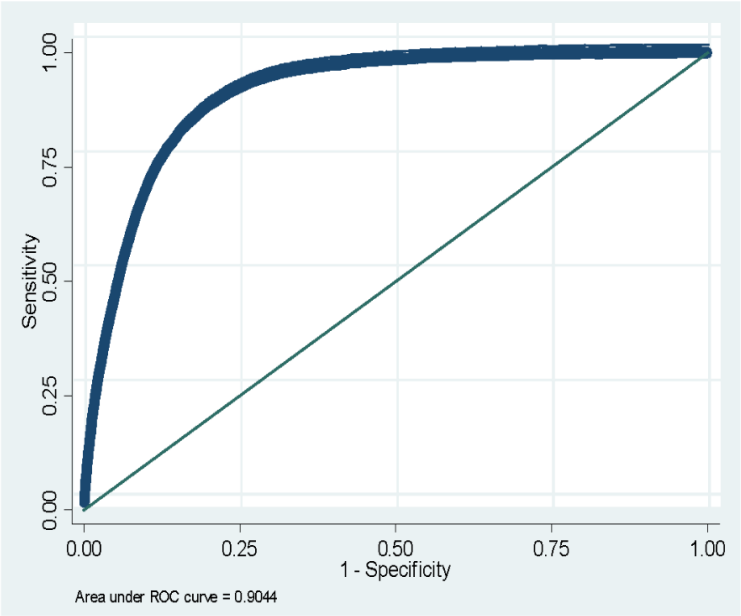
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth)



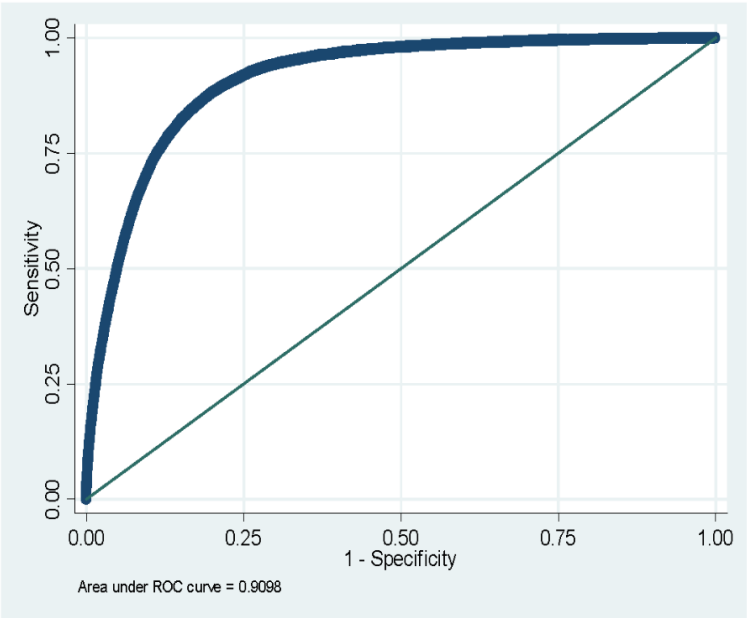
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + at least one comorbidity



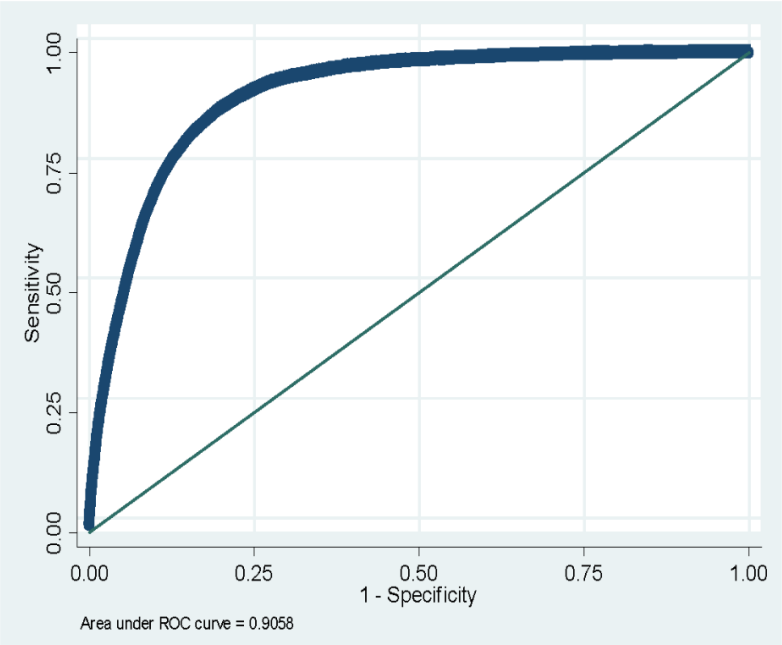
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + count of comorbidities



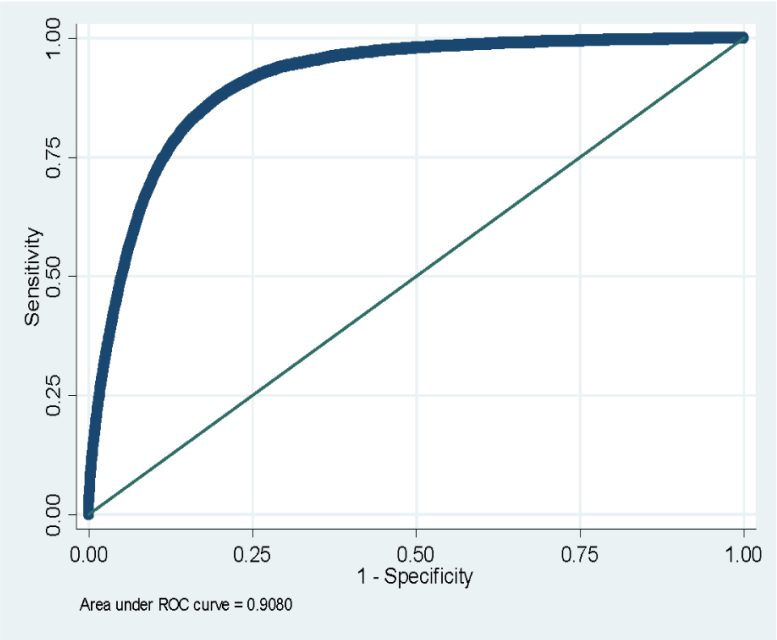
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + all 31 comorbidities added as binary variables at the same time



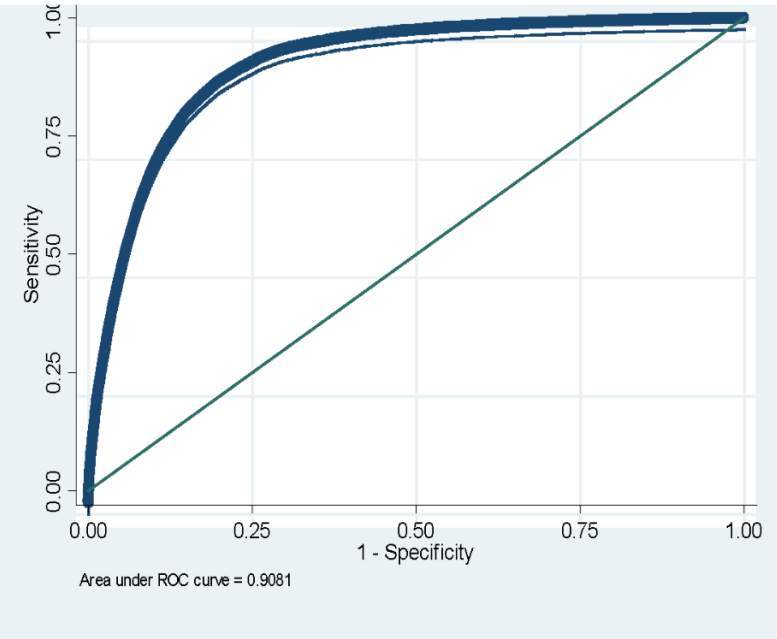
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + Charlson Comorbidity Index (CCI)



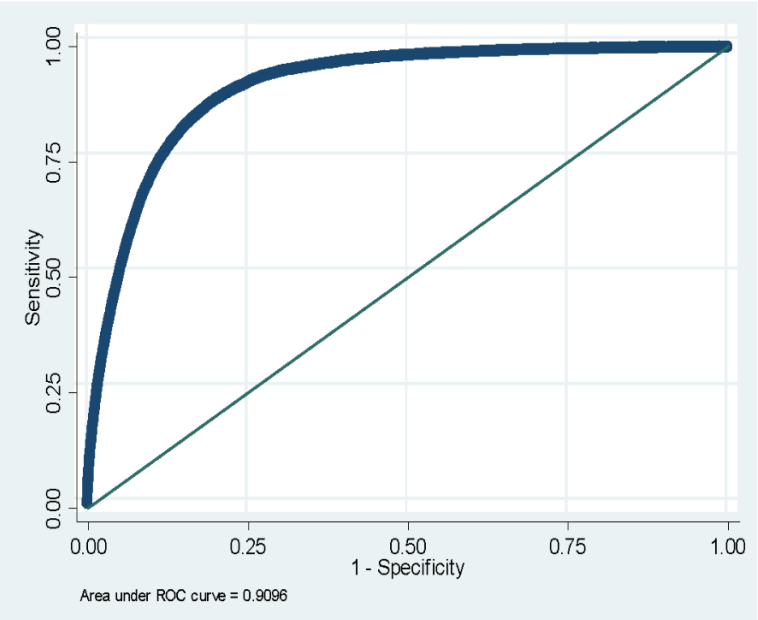
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + CCI updated by Quan et al. 2005



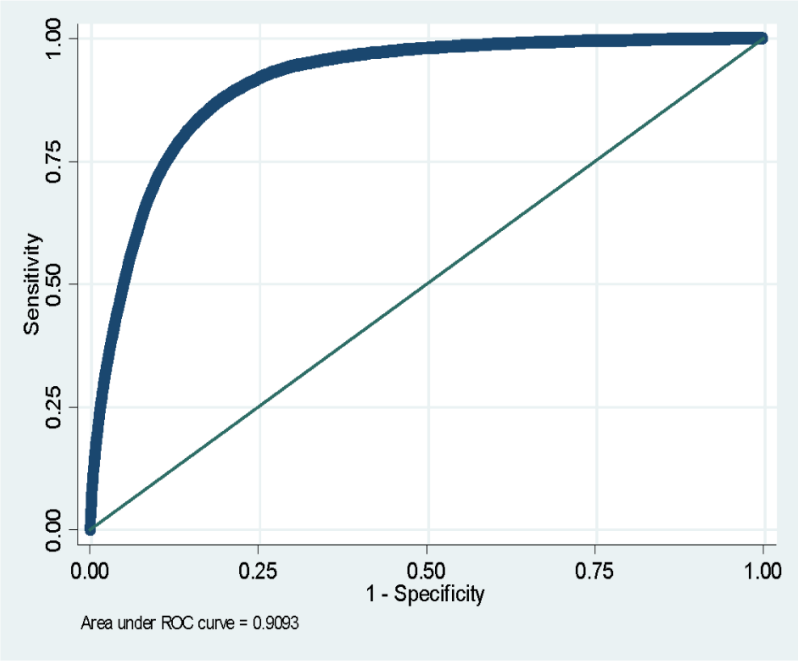
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + Elixhauser Comorbidity Measure (ECM)



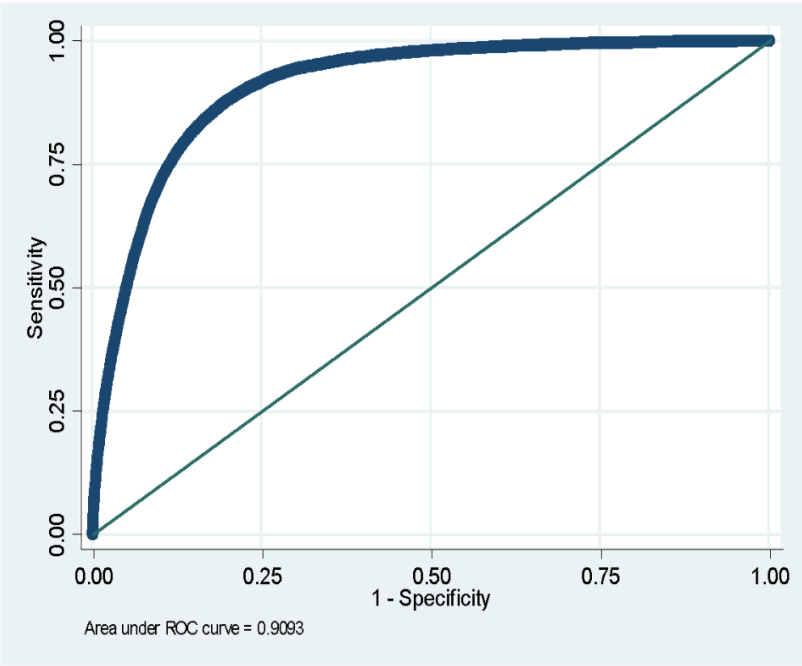
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + AICI-1yr (binary comorbidity index with 19 conditions)



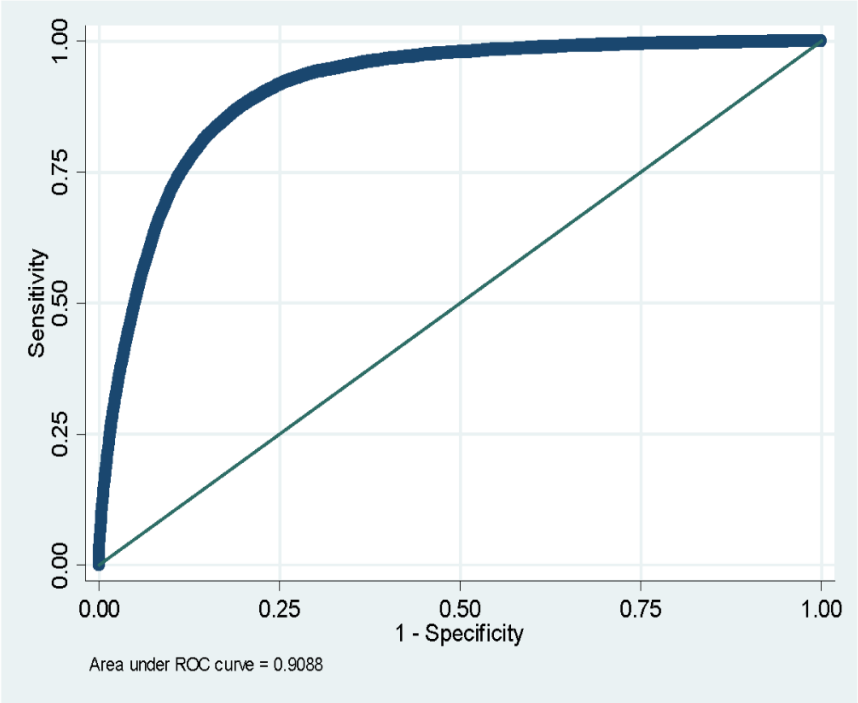
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + comorbidity index with actual weights (19 conditions)



Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + comorbidity index with rounded weights (19 conditions)

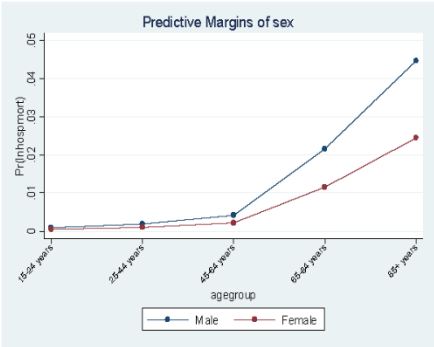


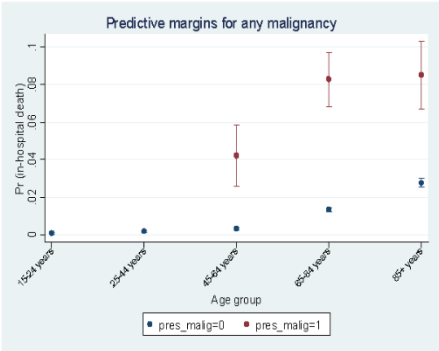
Baseline model (age, sex, injury-severity, injury-type, body region, geographic region, socio-economic group and country of birth) + AICI-m (parsimonious comorbidity index with 10 conditions)

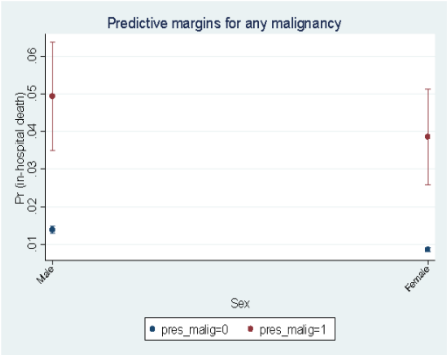


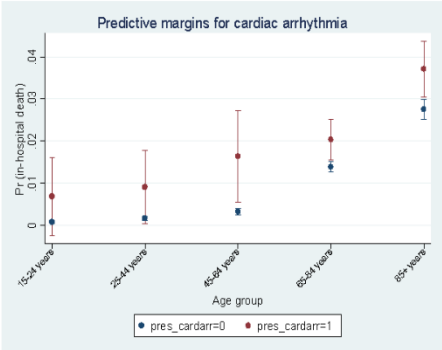
Appendix E2 – Interaction plots

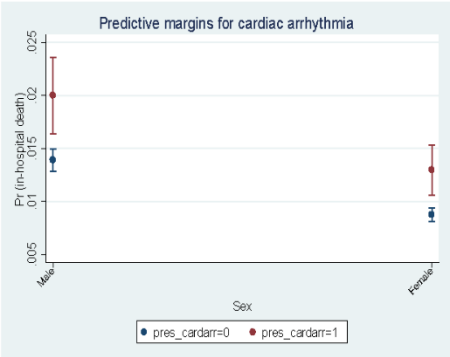
In-hospital death

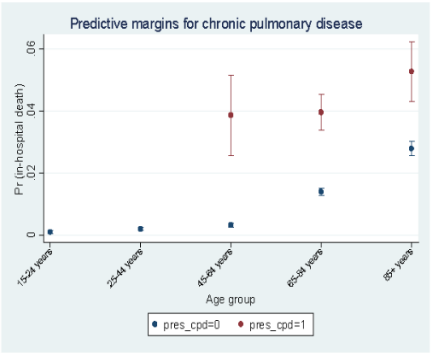


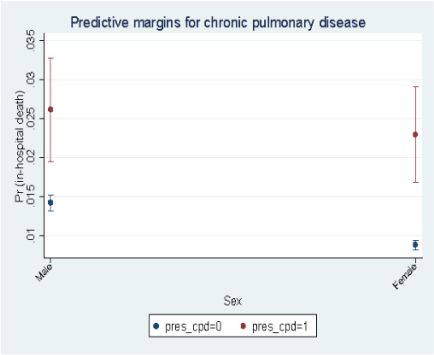


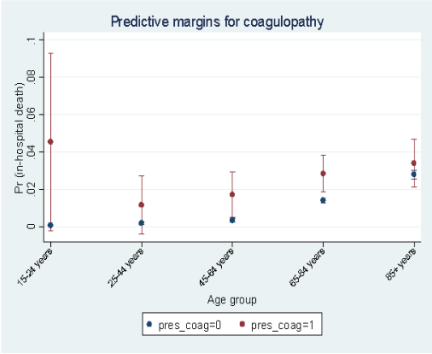


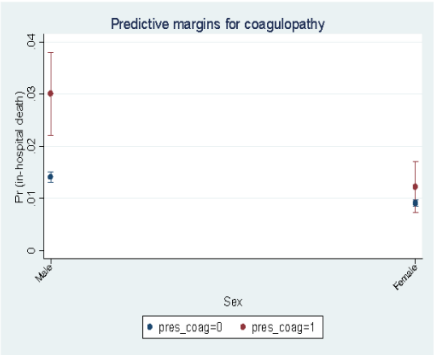


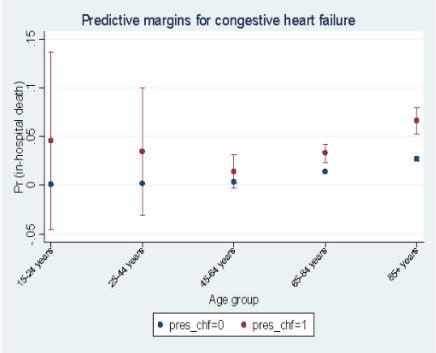


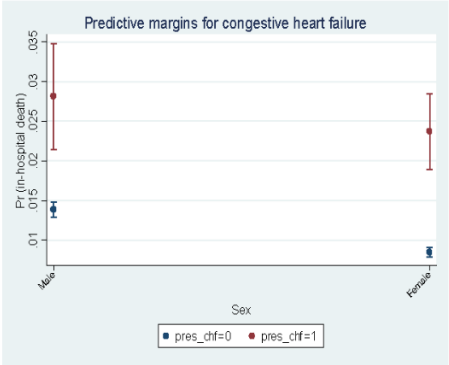

Predictive margins for chronic pulmonary disease
Pr (in-hospital death)
0
.02
.04
.06
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

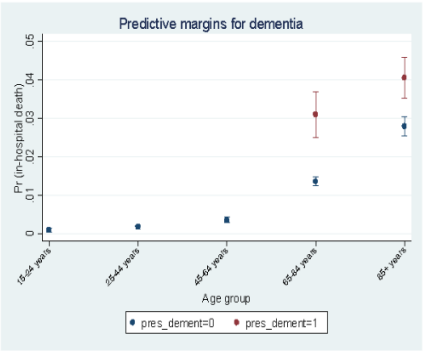

Predictive margins for chronic pulmonary disease
Pr (in-hospital death)
.01
.015
.02
.025
.03
.035
Male
Female
Sex
pres_cpd=0
pres_cpd=1

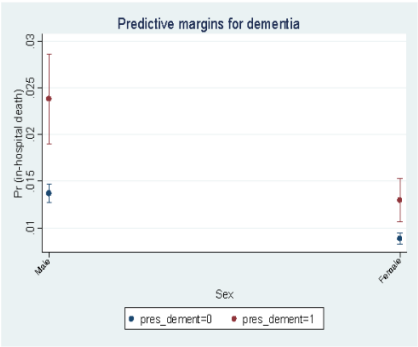

Predictive margins for coagulopathy
Pr (in-hospital death)
0
.02
.04
.06
.08
.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

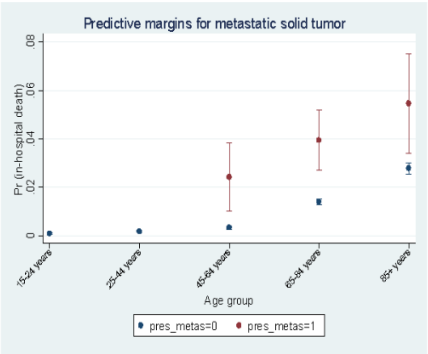

Predictive margins for coagulopathy
Pr (in-hospital death)
0
.01
.02
.03
.04
Male
Female
Sex
pres_coag=0
pres_coag=1

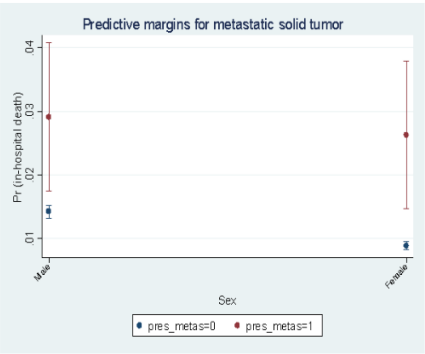

Predictive margins for congestive heart failure
Pr (in-hospital death)
-.05
0
.05
.1
.15
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

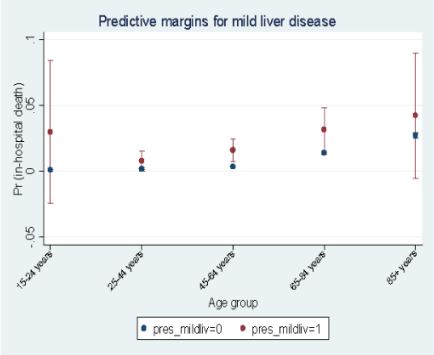

Predictive margins for congestive heart failure
Pr (in-hospital death)
.01
.015
.02
.025
.03
.035
Male
Female
Sex
pres_chf=0
pres_chf=1

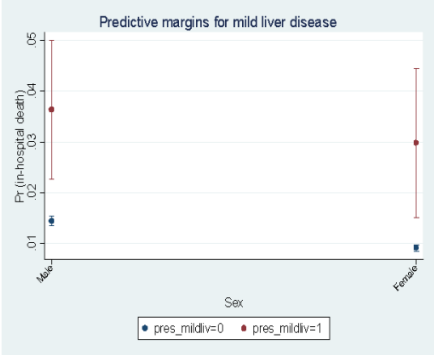

Predictive margins for dementia
Pr (in-hospital death)
0
.01
.02
.03
.04
.05
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1

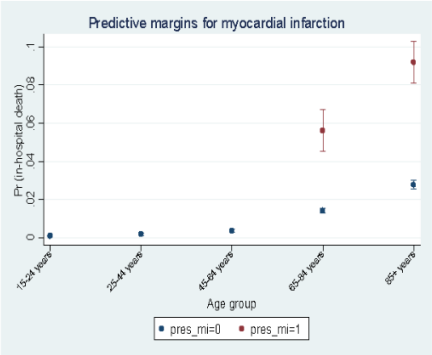

Predictive margins for dementia
Pr (in-hospital death)
.01
.015
.02
.025
.03
Male
Female
Sex
pres_dement=0
pres_dement=1

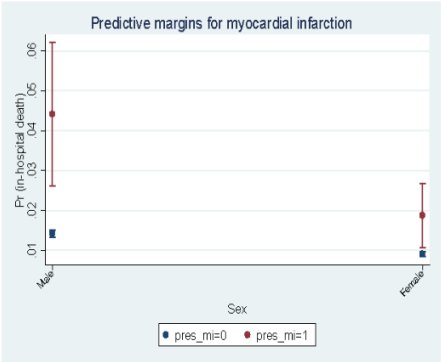

Predictive margins for metastatic solid tumor
Pr (in-hospital death)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_metas=0
pres_metas=1

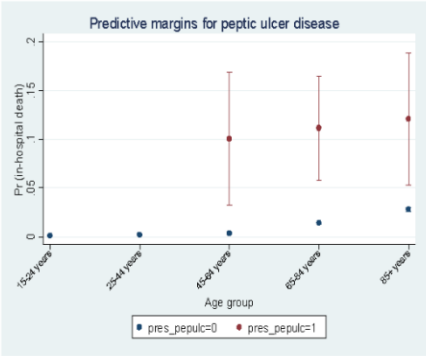

Predictive margins for metastatic solid tumor
Pr (in-hospital death)
.01
.02
.03
.04
Male
Female
Sex
pres_metas=0
pres_metas=1

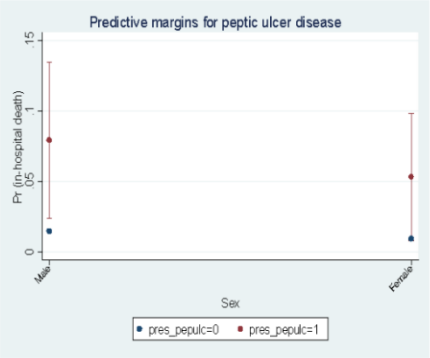

Predictive margins for mild liver disease
Pr (in-hospital death)
-.05
0
.05
.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1

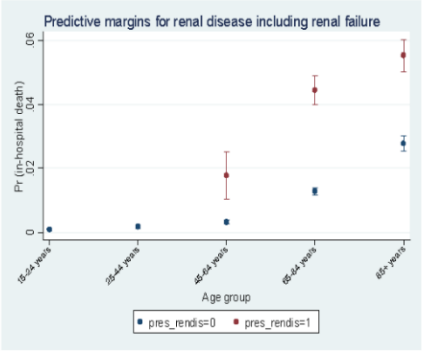

Predictive margins for mild liver disease
Pr (in-hospital death)
.01
.02
.03
.04
.05
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

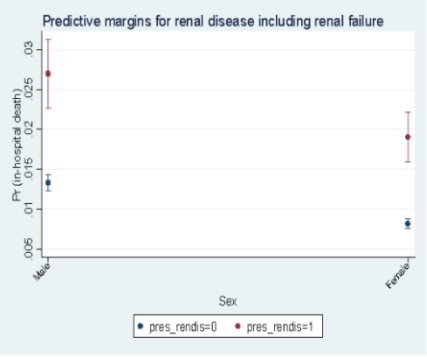

Predictive margins for myocardial infarction
Pr (in-hospital death)
0
.02
.04
.06
.08
.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mi=0
pres_mi=1


Predictive margins for myocardial infarction
Pr (in-hospital death)
.01
.02
.03
.04
.05
.06
Male
Female
Sex
pres_mi=0
pres_mi=1

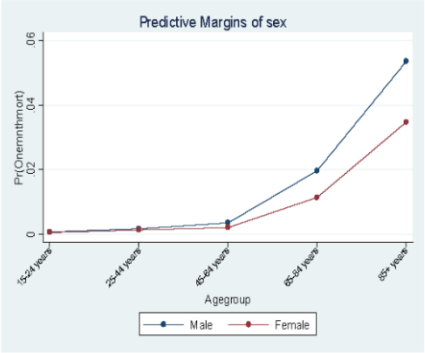


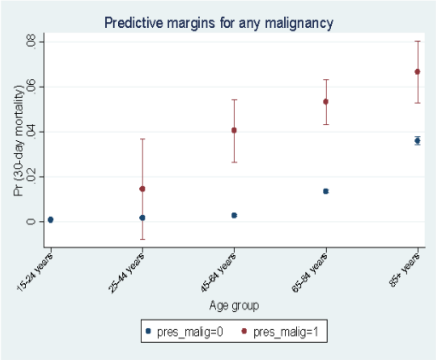


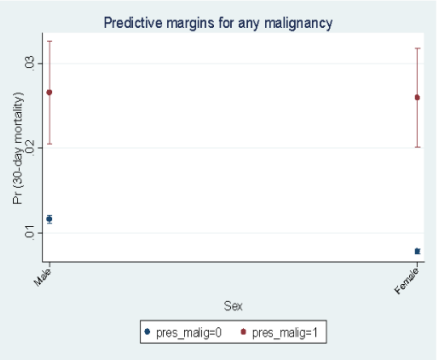


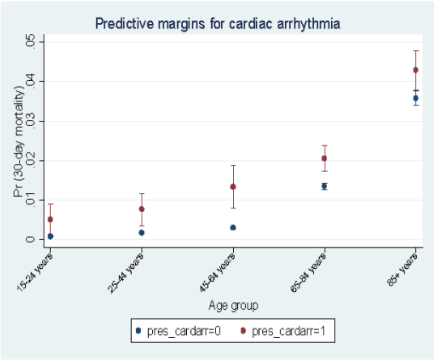


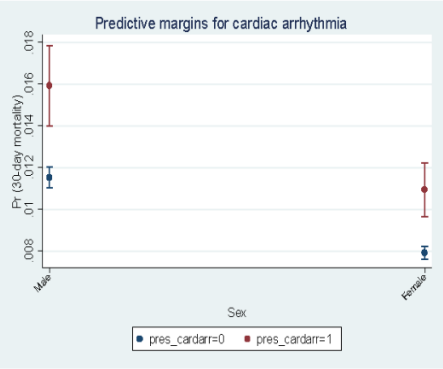
30-day mortality

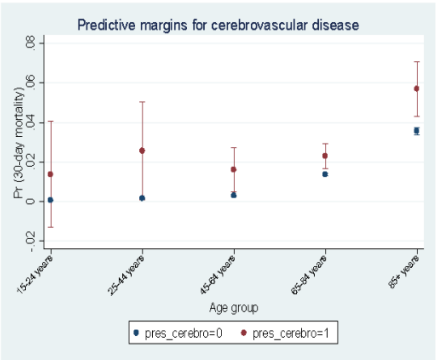


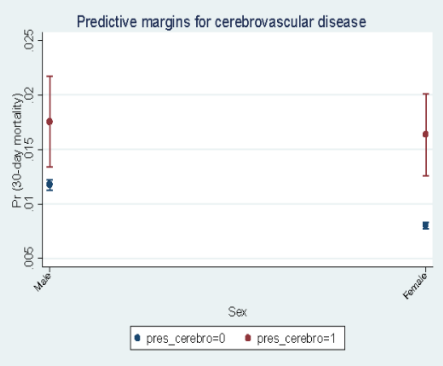

Predictive margins for any malignancy
Pr (30-day mortality)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_malig=0
pres_malig=1

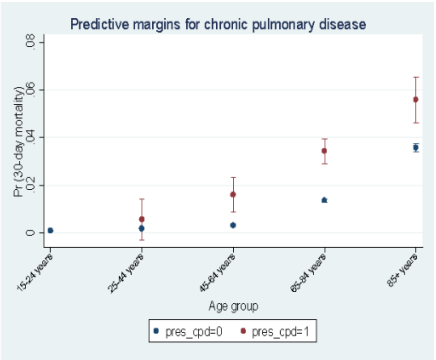

Predictive margins for any malignancy
Pr (30-day mortality)
.01
.02
.03
Male
Female
Sex
pres_malig=0
pres_malig=1

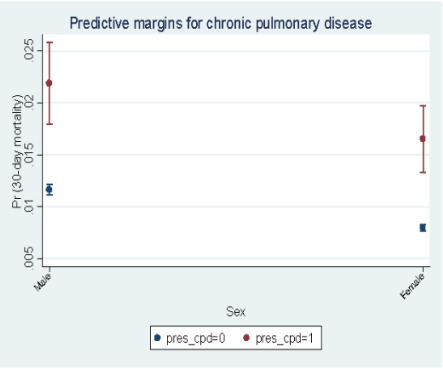

Predictive margins for cardiac arrhythmia
Pr (30-day mortality)
0
.01
.02
.03
.04
.05
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cardarr=0
pres_cardarr=1

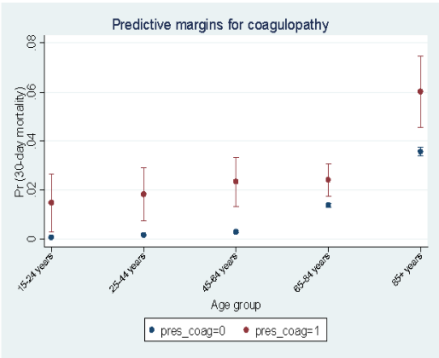

Predictive margins for cardiac arrhythmia
Pr (30-day mortality)
.008
.01
.012
.014
.016
.018
Male
Female
Sex
pres_cardarr=0
pres_cardarr=1

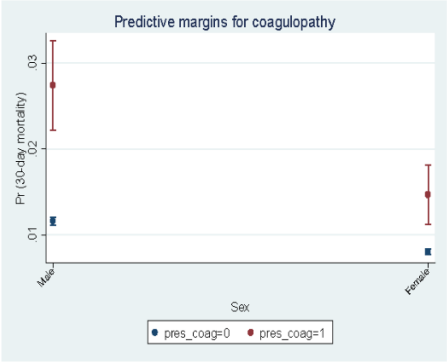

Predictive margins for cerebrovascular disease
Pr (30-day mortality)
-.02
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cerebro=0
pres_cerebro=1

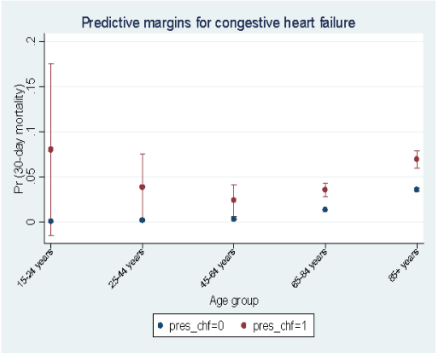

Predictive margins for cerebrovascular disease
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_cerebro=0
pres_cerebro=1

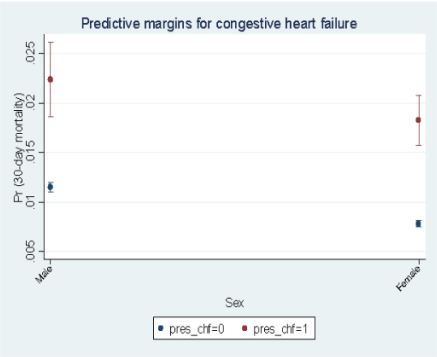

Predictive margins for chronic pulmonary disease
Pr (30-day mortality)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

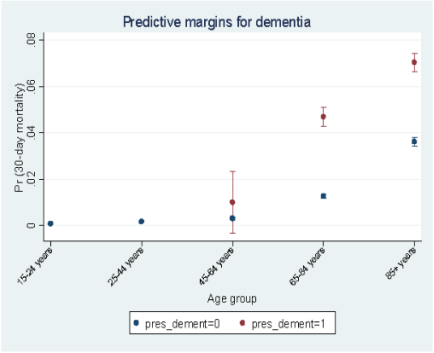

Predictive margins for chronic pulmonary disease
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_cpd=0
pres_cpd=1

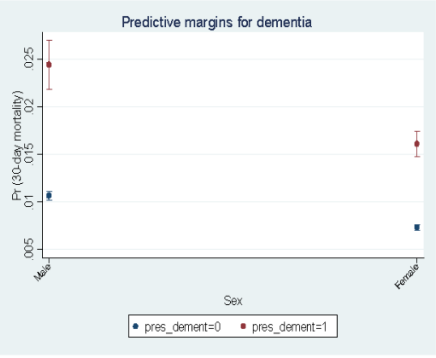

Predictive margins for coagulopathy
Pr (30-day mortality)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

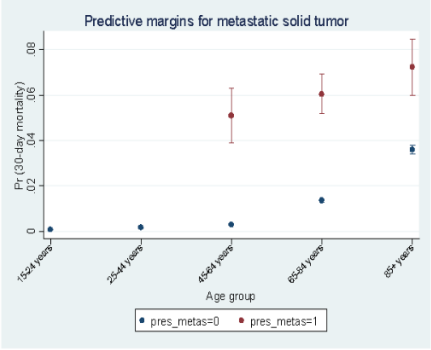

Predictive margins for coagulopathy
Pr (30-day mortality)
.01
.02
.03
Male
Female
Sex
pres_coag=0
pres_coag=1

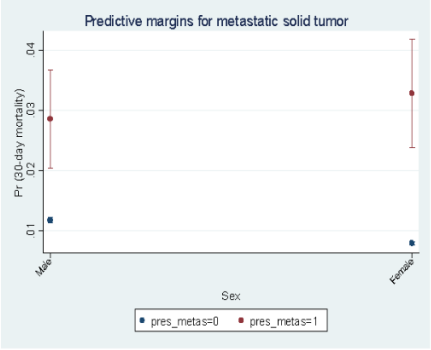

Predictive margins for congestive heart failure
Pr (30-day mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

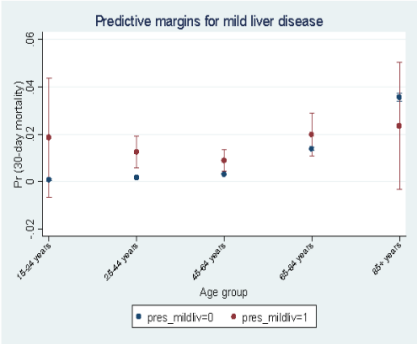

Predictive margins for congestive heart failure
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_chf=0
pres_chf=1

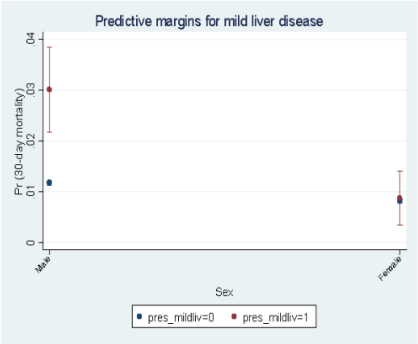

Predictive margins for dementia
Pr (30-day mortality)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1


Predictive margins for dementia
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_dement=0
pres_dement=1

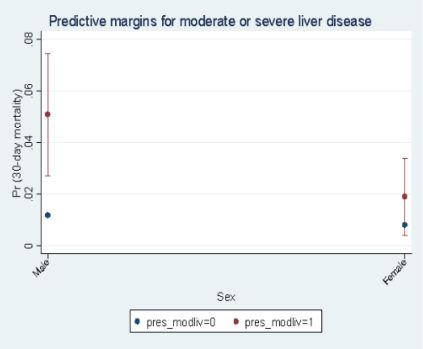

Predictive margins for metastatic solid tumor
Pr (30-day mortality)
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_metas=0
pres_metas=1

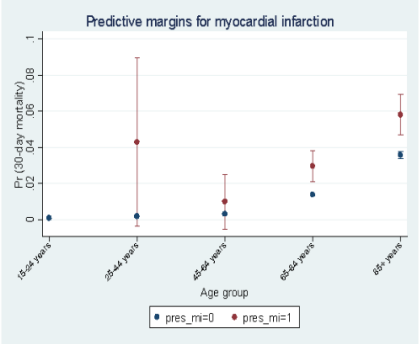

Predictive margins for metastatic solid tumor
Pr (30-day mortality)
.01
.02
.03
.04
Male
Female
Sex
pres_metas=0
pres_metas=1

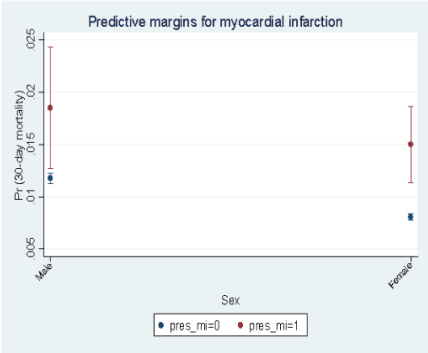

Predictive margins for mild liver disease
Pr (30-day mortality)
-.02
0
.02
.04
.06
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1

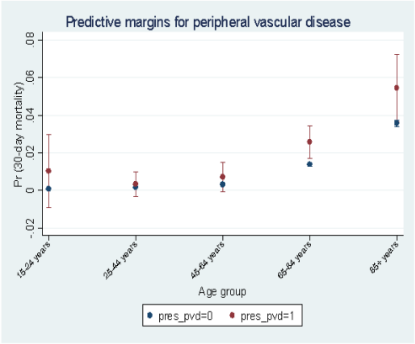

Predictive margins for mild liver disease
Pr (30-day mortality)
0
.01
.02
.03
.04
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

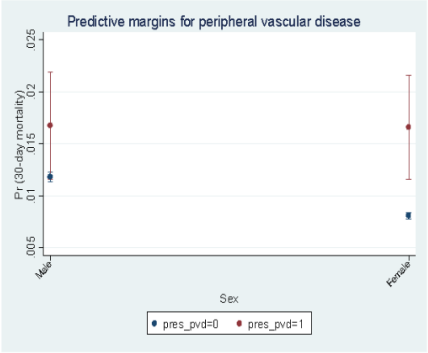

Predictive margins for moderate or severe liver disease
Pr (30-day mortality)
-.02
0
.02
.04
.06
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_modliv=0
pres_modliv=1

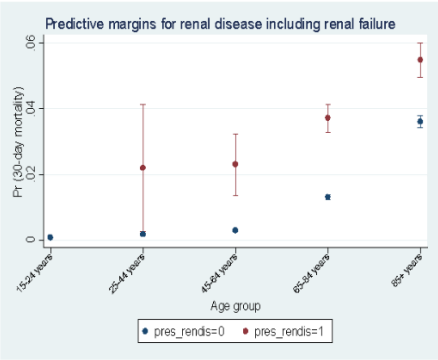

Predictive margins for moderate or severe liver disease
Pr (30-day mortality)
0
.02
.04
.06
.08
Male
Female
Sex
pres_modliv=0
pres_modliv=1

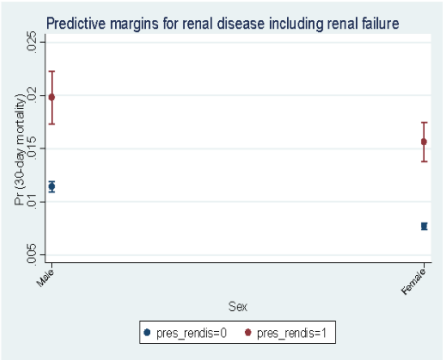

Predictive margins for myocardial infarction
Pr (30-day mortality)
0
.02
.04
.06
.08
.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mi=0
pres_mi=1


Predictive margins for myocardial infarction
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_mi=0
pres_mi=1

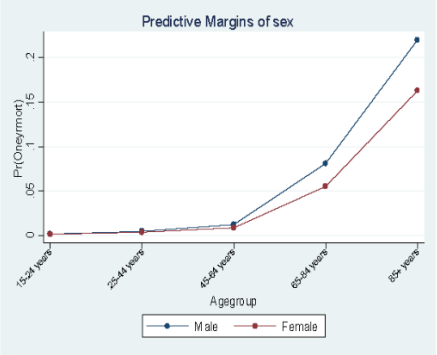

Predictive margins for peripheral vascular disease
Pr (30-day mortality)
-.02
0
.02
.04
.06
.08
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pvd=0
pres_pvd=1

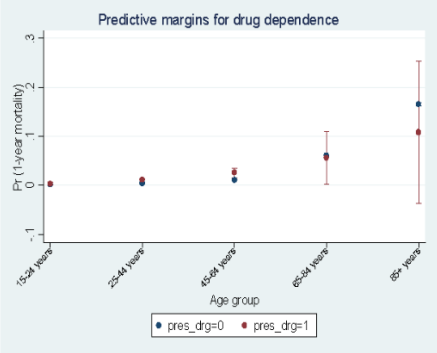

Predictive margins for peripheral vascular disease
Pr (30-day mortality)
.005
.01
.015
.02
.025
Male
Female
Sex
pres_pvd=0
pres_pvd=1

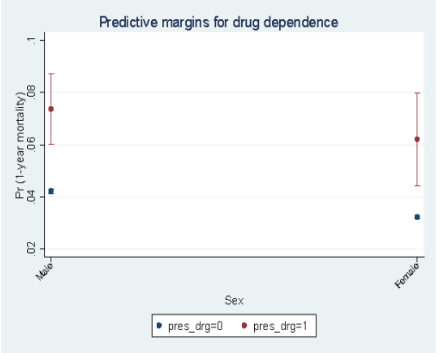


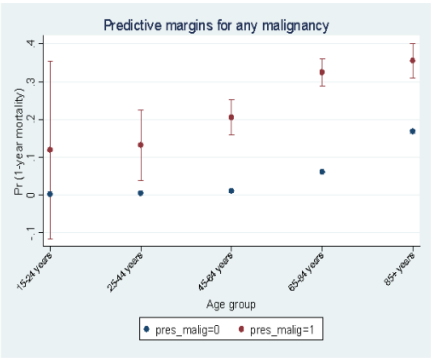


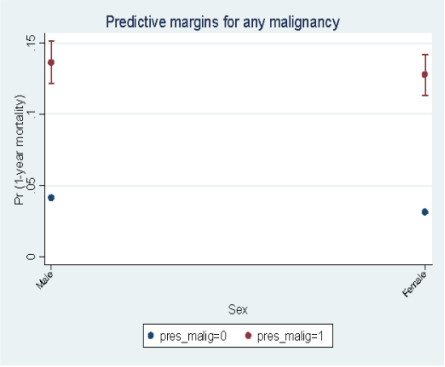
1-year mortality

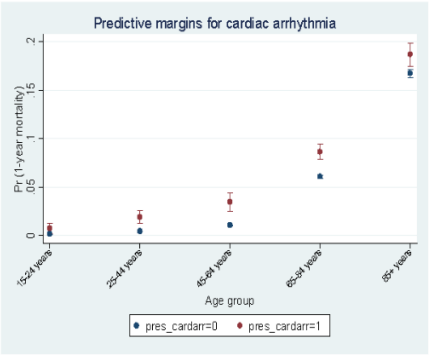


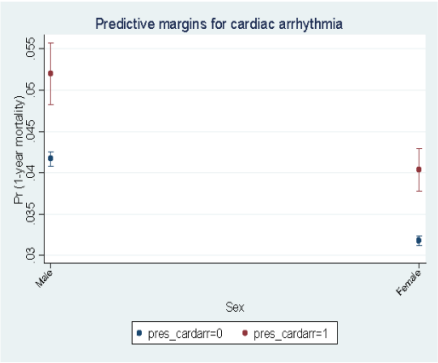


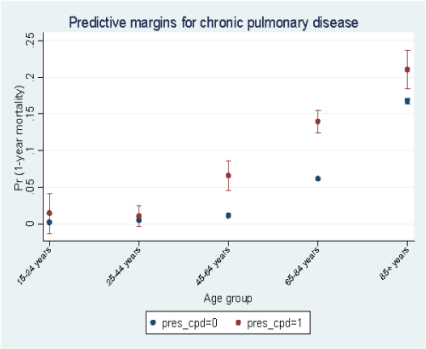


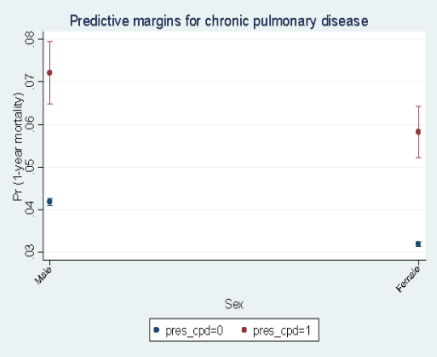

Predictive margins for any malignancy
Pr (1-year mortality)
-.1
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_malig=0
pres_malig=1

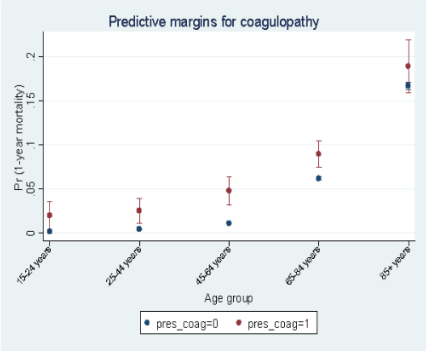

Predictive margins for any malignancy
Pr (1-year mortality)
0
.05
.1
.15
Male
Female
Sex
pres_malig=0
pres_malig=1

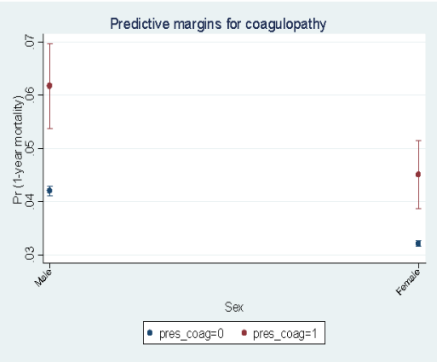

Predictive margins for cardiac arrhythmia
Pr (1-year mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cardarr=0
pres_cardarr=1

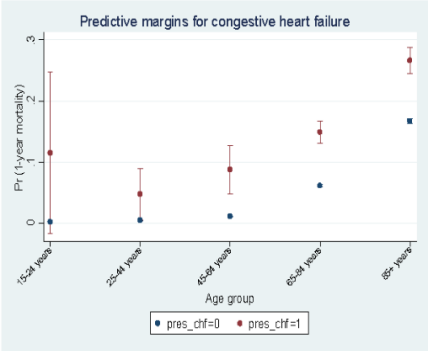

Predictive margins for cardiac arrhythmia
Pr (1-year mortality)
.03
.035
.04
.045
.05
.055
Male
Female
Sex
pres_cardarr=0
pres_cardarr=1

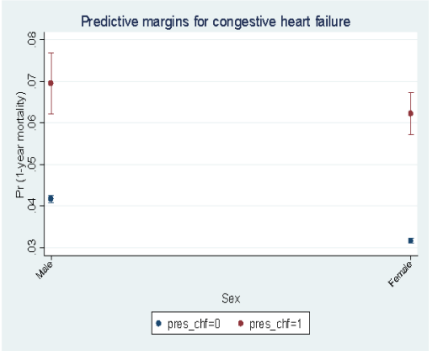

Predictive margins for chronic pulmonary disease
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

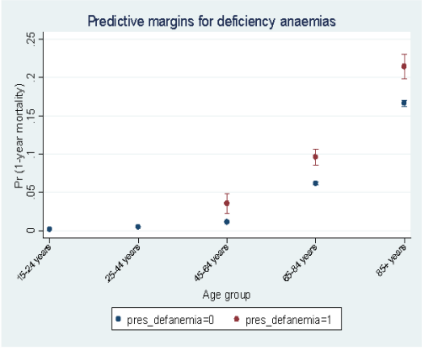

Predictive margins for chronic pulmonary disease
Pr (1-year mortality)
.03
.04
.05
.06
.07
.08
Male
Female
Sex
pres_cpd=0
pres_cpd=1

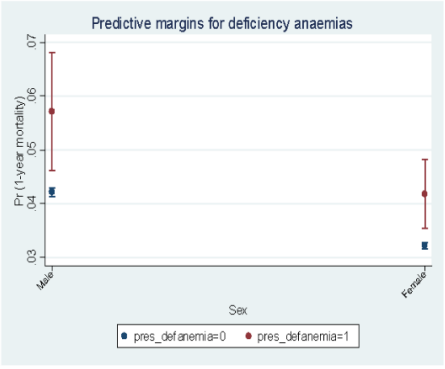

Predictive margins for coagulopathy
Pr (1-year mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

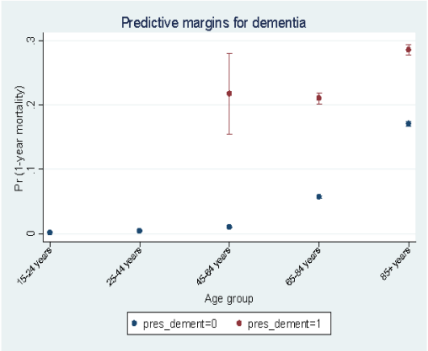

Predictive margins for coagulopathy
Pr (1-year mortality)
.03
.04
.05
.06
.07
Male
Female
Sex
pres_coag=0
pres_coag=1

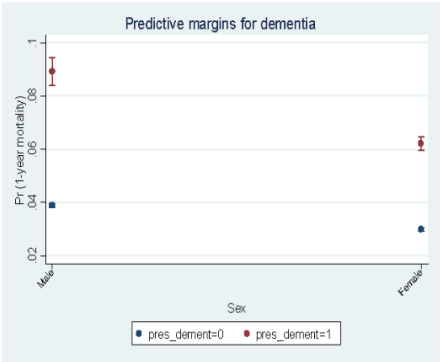

Predictive margins for congestive heart failure
Pr (1-year mortality)
0
1
2
3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

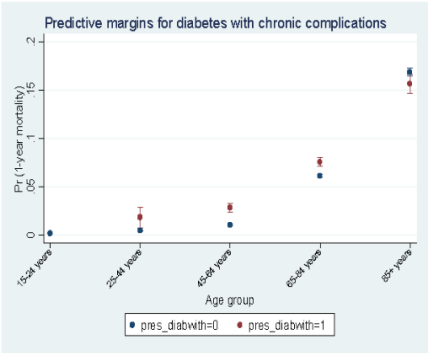

Predictive margins for congestive heart failure
Pr (1-year mortality)
.03
.04
.05
.06
.07
.08
Male
Female
Sex
pres_chf=0
pres_chf=1

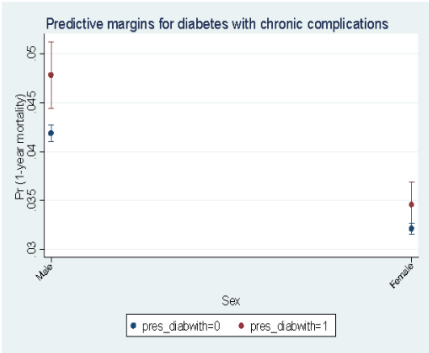

Predictive margins for deficiency anaemias
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_defanemia=0
pres_defanemia=1

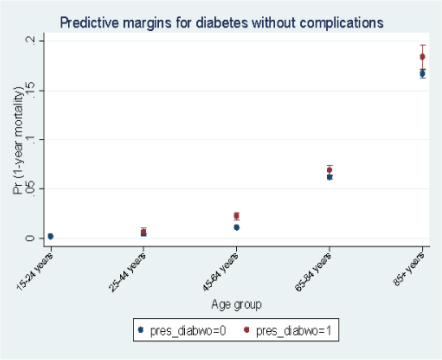

Predictive margins for deficiency anaemias
Pr (1-year mortality)
.03
.04
.05
.06
.07
Male
Female
Sex
pres_defanemia=0
pres_defanemia=1

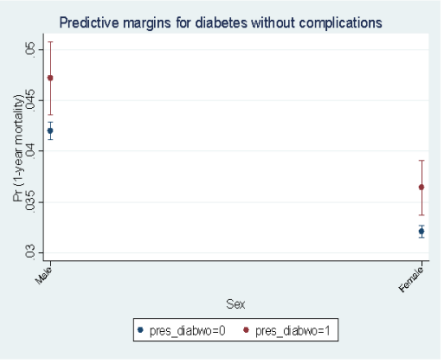

Predictive margins for dementia
Pr (1-year mortality)
0
1
2
3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1

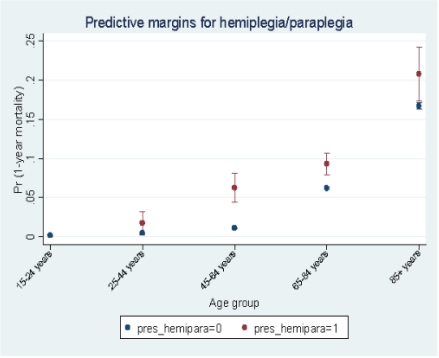

Predictive margins for dementia
Pr (1-year mortality)
.02
.04
.06
.08
.1
Male
Female
Sex
pres_dement=0
pres_dement=1

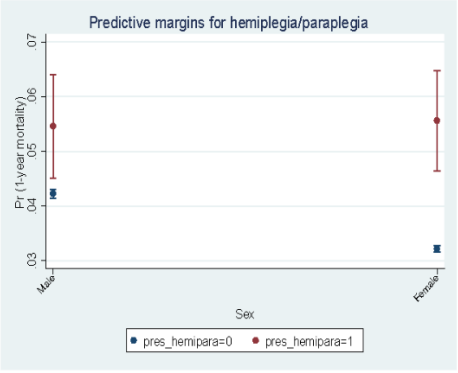

Predictive margins for diabetes with chronic complications
Pr (1-year mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

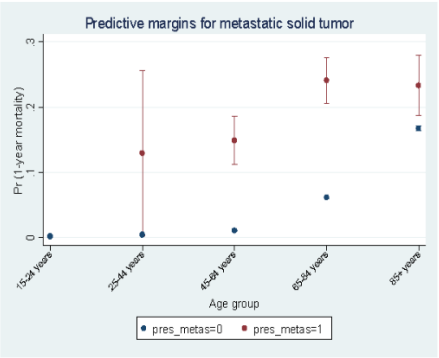

Predictive margins for diabetes with chronic complications
Pr (1-year mortality)
.03
.035
.04
.045
.05
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

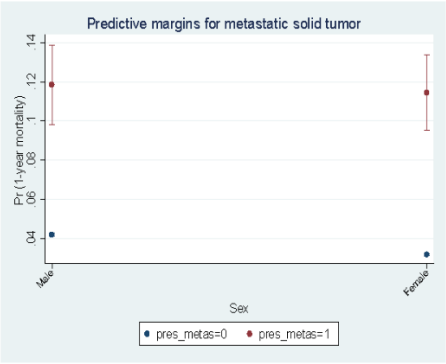

Predictive margins for diabetes without complications
Pr (1-year mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

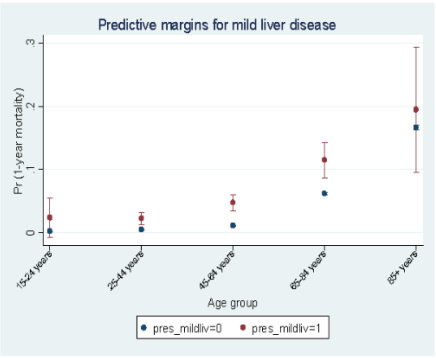

Predictive margins for diabetes without complications
Pr (1-year mortality)
.03
.035
.04
.045
.05
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

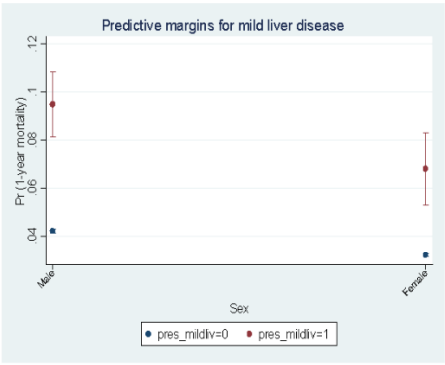

Predictive margins for hemiplegia/paraplegia
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hemipara=0
pres_hemipara=1

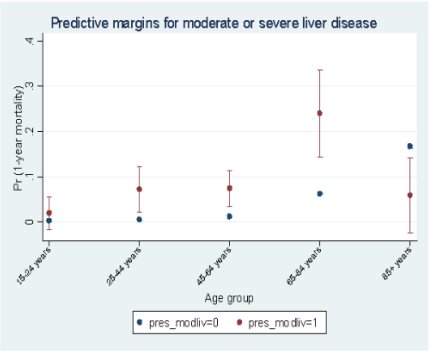

Predictive margins for hemiplegia/paraplegia
Pr (1-year mortality)
.03
.04
.05
.06
.07
Male
Female
Sex
pres_hemipara=0
pres_hemipara=1

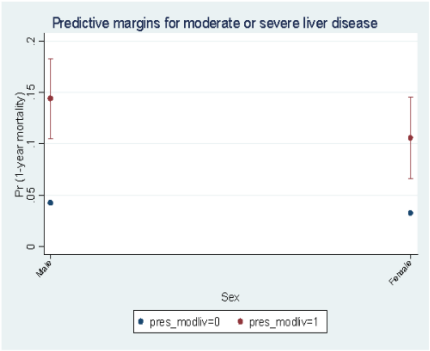

Predictive margins for metastatic solid tumor
Pr (1-year mortality)
0
.1
.2
.3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_metas=0
pres_metas=1

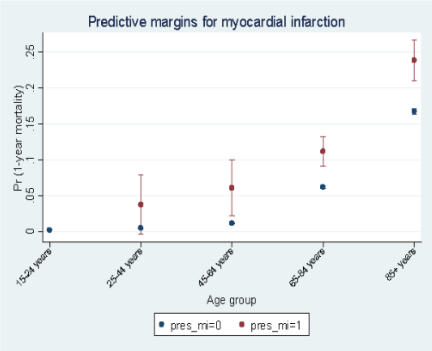

Predictive margins for metastatic solid tumor
Pr (1-year mortality)
.04
.06
.08
.1
.12
.14
Male
Female
Sex
pres_metas=0
pres_metas=1

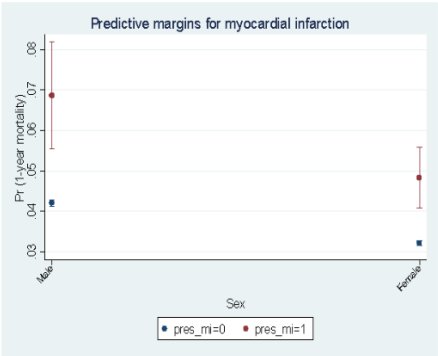

Predictive margins for mild liver disease
Pr (1-year mortality)
0
.1
.2
.3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1

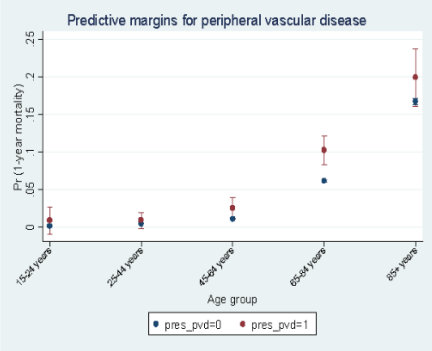

Predictive margins for mild liver disease
Pr (1-year mortality)
.04
.06
.08
.1
.12
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

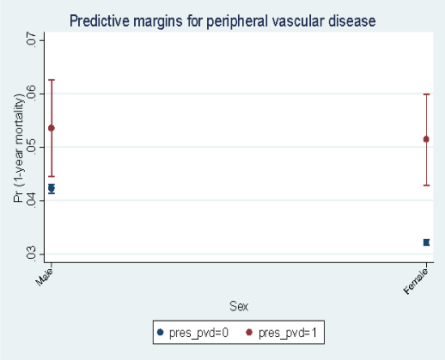

Predictive margins for moderate or severe liver disease
Pr (1-year mortality)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_modliv=0
pres_modliv=1

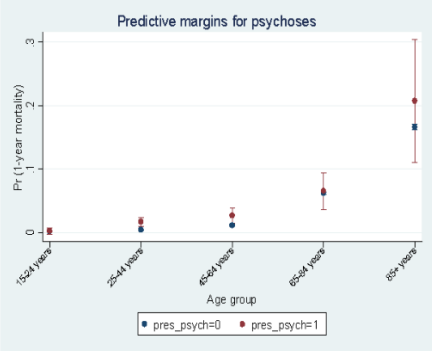

Predictive margins for moderate or severe liver disease
Pr (1-year mortality)
0
.05
.1
.15
.2
Male
Female
Sex
pres_modliv=0
pres_modliv=1

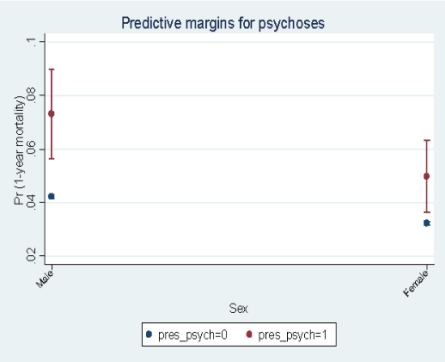

Predictive margins for myocardial infarction
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mi=0
pres_mi=1

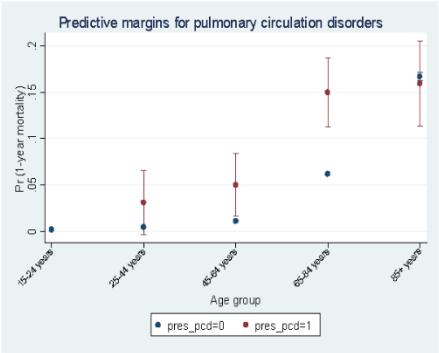

Predictive margins for myocardial infarction
Pr (1-year mortality)
.03
.04
.05
.06
.07
.08
Male
Female
Sex
pres_mi=0
pres_mi=1

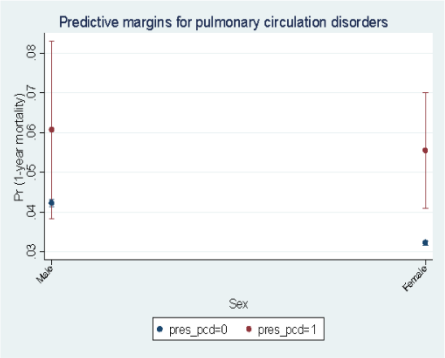

Predictive margins for peripheral vascular disease
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pvd=0
pres_pvd=1

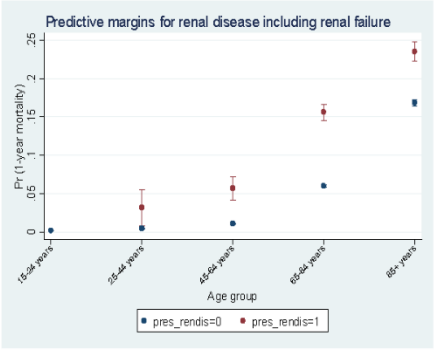

Predictive margins for peripheral vascular disease
Pr (1-year mortality)
.03
.04
.05
.06
.07
Male
Female
Sex
pres_pvd=0
pres_pvd=1

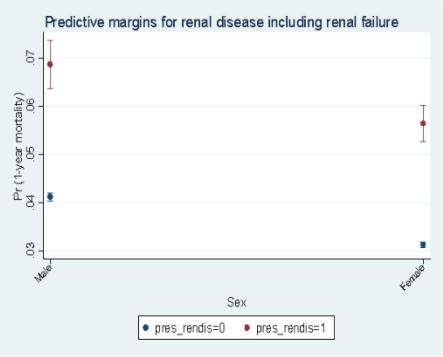

Predictive margins for psychoses
Pr (1-year mortality)
0
.1
.2
.3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_psych=0
pres_psych=1


Predictive margins for psychoses
Pr (1-year mortality)
.02
.04
.06
.08
.1
Male
Female
Sex
pres_psych=0
pres_psych=1


Predictive margins for pulmonary circulation disorders
Pr (1-year mortality)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pcd=0
pres_pcd=1


Predictive margins for pulmonary circulation disorders
Pr (1-year mortality)
.03
.04
.05
.06
.07
.08
Male
Female
Sex
pres_pcd=0
pres_pcd=1


Predictive margins for renal disease including renal failure
Pr (1-year mortality)
0
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rendis=0
pres_rendis=1


Predictive margins for renal disease including renal failure
Pr (1-year mortality)
.03
.04
.05
.06
.07
Male
Female
Sex
pres_rendis=0
pres_rendis=1

Appendix E3 – Results

Detailed discussion based on the multivariable regression modelling

1 Australian Injury Comorbidity Indices (AICIs)

1.1 In hospital death

Based on the lowest AIC, the best fit for in-hospital death was model number *vi* (containing the ECM (AIC=12371)), followed by model *x* (containing all 31 comorbidities (AIC=12434)) and model *xi* (selected 11 comorbidities with actual weights (AIC=12446)) (Table 3 & Table E3). The AIC for model *ii* (containing the AICI-hd) was 12458, implying that the model with actual weights fit better than the model with binary representation of comorbidities. Model *iv* (using the CCI) had the poorest model fit (AIC=12675). The CIs for the AUC statistics for all these models (except the baseline) overlap, indicating that there is no significant difference between the predictive powers of the various indices (AUC containing ECM 0.924 (CI 0.919-0.929), containing CCI 0.915 (CI 0.909-0.920), containing all 31 conditions 0.922 (CI 0.917-0.927) and containing the selected 11 conditions 0.920 (CI 0.915-0.925)). This implies, that using the index with a binary representation of the 11 selected conditions will yield a better fit than the CCI, uses lesser conditions than both the CCI and ECM and retains an equal predictive power, and is better than the baseline model.

1.2 30-day Mortality

Based on the lowest AICs, the best fit for 30-day mortality was model *xi* (containing the selected 13 conditions with actual weights (AIC=39924)) followed by model *x* (containing all 31 comorbidities (AIC=39933)) (Table 3 & Table E3); The AIC for model *ii* (containing the AICI-30d) was 39939, implying that the model with actual weights fit better than the model with binary representation of comorbidities. Model *iv* (containing the CCI) had the poorest

model fit (AIC=40543). The predictive powers of model *ii* (AUC of 0.923 (CI 0.920-0.926)) vs. models *x* (AUC of 0.924 (CI 0.921-0.926)), *iv-vi* (CCI (AUC of 0.919 (CI 0.916-0.922)), updated CCI (AUC of 0.920 (CI 0.917-0.923)) and ECM (AUC of 0.923 (CI 0.920-0.925))) are similar (overlapping CIs for the AUC statistics) (Table 3). As in the case of in-hospital death, all of the above implies, that using the index with a binary representation of the 13 selected conditions will yield a better fit than the CCI, uses lesser conditions than both the CCI and ECM and retains an equal predictive power, and is better than the baseline model for capturing comorbidity when predicting 30-day mortality.

Even though model with actual weights (model *xi*s) fits the data better than model with binary representations (model *ii*s) for both in-hospital death and 30-day mortality, given that there is no significant difference in predictive power, the use of the simpler binary indices can be recommended.

1.3 One-year mortality

Based on the lowest AIC, the best fit for 1-year mortality was model number *x* (containing all 31 comorbidities (AIC=109040)) (Table E3) followed by model *ii* (containing the AICI-1-yr (AIC=109065)) (Table 3). The AIC for the CCI (AIC=110810), updated CCI (AIC=109704) and ECM (109962) were much higher than the study derived indices. The differences between the predictive powers of model *ii* (AUC of 0.910 (CI 0.908-0.911) vs. models *iv* (AUC of CCI-0.906 (CI 0.904-0.908)), *v* (AUC of updated CCI-0.908 (CI 0.906-0.910)), *vi* (AUC of ECM-0.908 (CI 0.906-0.910)) and *x* (0.910 (CI 0.908-0.912)) were negligible (overlapping CIs). Model *x* includes all 31 comorbidities regardless of their significance to the outcomes, whereas model *ii* includes only conditions relevant to the outcome (i.e., exclude conditions that do not provide further improvement to model-fit). The above implies, that using the index with a binary representation of the 19 selected conditions will yield a better fit than the CCI or ECM,

uses lesser conditions than the ECM and retains an equal predictive power, and is better than the baseline model for capturing comorbidity when predicting 1-year mortality.

2 Interaction effects

Interaction effects between comorbidities, age and gender, were also modelled. The selection of these specific interaction variables was due to the expectation that the severity and impact of comorbidity can vary with age and gender. The age-sex interaction was not significant. Age-comorbidity interaction was mostly observed in the older age-groups (see Appendix E2 for interaction plots). Sex-comorbidity interaction was seen for most comorbidities but the effect was not as pronounced as in the age-comorbidity interactions. All interaction terms provided very little or no improvement to the predictive ability of the models and were therefore excluded from the analysis. A set of comorbidity indices were derived especially for the 65 and above age group to address the age-comorbidity interaction effect (Table E5).

3 The advantage of the binary index over the weighted index

When modeling the weighted index, there were no differences in the predictive power of the model with rounded weights (integers) (Table 3 model *iii*) vs. the exact value (Table E3 model *xi*). Therefore, in finalising the weighted models, the rounded ORs were used. The binary index has an added advantage over the weighted index: the binary index checks for the independent effect of each condition whilst the weighted index simply looks at an overall summed score. An overall score in certain instances can mislead outcome prediction, i.e., a patient with multiple non-life-threatening comorbidities can have the same score as a patient with a single life-threatening comorbidity, whereby both patients will have an equally likely prediction of death when employing a weighted index.

4 Comorbidity indices derived using all age groups

Comorbidity indices were also derived with children included. The results were quite similar to the adult indices; only minor differences were observed in the AUC statistics and false negative rates. The only notable difference was the exclusion of metastatic solid tumor and the increase in weight for 'any malignancy' for in-hospital death. This exclusion results in the condition being eliminated from the parsimonious index as well.

5 Comorbidity indices derived using older adults (age >=65 years)

The necessity for a specific comorbidity index for the older adults was seen only for predicting in-hospital death (Table 5). The false negative rates were significantly lower in the new age-specific index than the general or parsimonious index and the CCI, while there was no statistical difference with the ECM. For 30-day and 1-year mortality, the new age-specific index had significantly lower false negative rates than the CCI but not significantly lower false negative rates than the ECM or the general indexes. As a measure of capturing comorbidity, the newly derived non-age-specific binary or parsimonious indices are most suitable as they are more concise, improve model fit and includes comorbidities relevant to outcome compared to existing indices.

6 External validations

Assessing model performance, the AUC statistics indicate that the binary index (AUC of 0.914 (CI 0.910-0.918), 0.901 (CI 0.898-0.903) and 0.893 (CI 0.891-0.894)) for in-hospital death, 30-day and 1-year mortality and the parsimonious index (AUC of 0.914 (CI 0.909-0.918), 0.900 (CI 0.897-0.902) and 0.892 (CI 0.891-0.893)) both performed equally to the CCI (AUC of 0.908 (CI 0.904-0.913), 0.896 (CI 0.894-0.899) and 0.889 (CI 0.888-0.890)) and ECM (AUC of 0.917 (CI 0.913-0.921), 0.901 (CI 0.898-0.903) and 0.891 (CI 0.890-0.893)), except that the

binary and the parsimonious indices performed better than the CCI for 1-year mortality (Table E7). Tests of proportions show that the false negative rates were not significantly different between the binary indices (16.8%, 18.7% and 18.3%), parsimonious index (16.8%, 18.9% and 18.4%), the CCI (17.4%, 18.8% and 18.6%) and ECM (16.9%,18.4% and 18.4%) for in-hospital death, 30-day and 1-year mortality (Table 5).

Overall, the new indices performed just as well as the CCI and the ECM in terms of predictive power (AUCs). In terms of model fit (AIC statistic), the binary indices and the parsimonious index outperformed the existing indices, except for in-hospital death, where the ECM had the best model fit. NSW data provided similar results to the Victorian data. This confirms the findings from the Victorian data on an external dataset, thereby demonstrating the robustness of the new injury comorbidity indices.

Appendix E4 – Using the Australian Injury Comorbidity Indices

The Australian Injury Comorbidity Indices for mortality are recommended for use in epidemiological research where mortality is an outcome of interest.

Option I

The optimal use of these indices is made if the presence of each comorbidity is modelled (as a dummy variable with 1 for disease presence and 0 for absence) along with other main effects. Their best utility will be for death within 1-365 days. If used for mortality prediction, the lowest false negative rates are also achieved by this method. Note that the conditions included in the indices vary with the outcome, unless the more parsimonious index is used.

Option II

The other option is to use a score derived by adding the presence/absence of conditions for each index as shown in Table AA.1. The total score derived is used as the comorbidity indicator. Table AA.2 shows the scores for the Victorian study population based on percentiles. In prediction modelling, this option results in lower predictive power for the three mortality outcomes, higher false negative rates for in-hospital death and 1-year mortality, and lower false negative rates for 30-day mortality compared to option I.

Option II would be more useful in a clinical setting where patient classification is required, in the absence of retrospective data. The use of this score would need significant validations before it can be reliably used.

Table AA.1: Index calculation for a general injury patient cohort (all ages)

Comorbidity	In-hospital death	30-day mortality	1-year mortality	Parsimonious index
HIV/AIDS				
Alcohol dependence				
Drug dependence			1	
Any malignancy	1	1	1	1
Blood loss anaemia				

Cardiac arrhythmia	1	1	1	1
Cerebrovascular disease		1		
Chronic pulmonary disease	1	1	1	1
Coagulopathy	1	1	1	1
Congestive heart failure	1	1	1	1
Deficiency anaemias			1	
Dementia	1	1	1	1
Depression				
Diabetes with chronic complications			1	
Diabetes without complications			1	
Hemiplegia/paraplegia			1	
Hypertension complicated				
Hypertension uncomplicated				
Hypothyroidism				
Metastatic solid tumor	1	1	1	1
Mild liver disease	1	1	1	1
Moderate or severe liver disease		1	1	
Myocardial infarction	1	1	1	1
Obesity				
Peptic ulcer disease	1			
Peripheral vascular disease		1	1	
Psychoses			1	
Pulmonary circulation disorders			1	
Renal disease including renal failure	1	1	1	1
Rheumatic disease including some other connective tissue disorders				
Valvular disease				
Maximum total comorbidity score	11	13	19	10

Table AA.2: Minimum and maximum scores for injury comorbidity indices at selected percentiles for the Victorian cohorts (age >15 years)

Percentile	Cohort 1		Cohort 2		
	AICI-hd	AICI-m	AICI-30d	AICI-1yr	AICI-m
25th					
50th					
75th					
0-89th				0-0	
90th				1-1	
0-91st	0-0	0-0			
91st	1-1	1-1			
0-93rd			0-0		
94th			1-1		
0-94th					0-0
95th					1-1
98th				2-2	
99th	2-2	2-2	2-2		
100th	3-5	3-5	3-6	3-8	2-6

Table AA.3: Index calculation for a general injury patient cohort (above 64 years of age)

Comorbidity	In-hospital death	30-day mortality	1-year mortality	Parsimonious index
HIV/AIDS				
Alcohol dependence		1	1	
Drug dependence				
Any malignancy	1	1	1	1
Blood loss anaemia				
Cardiac arrhythmia	1	1	1	1
Cerebrovascular disease				
Chronic pulmonary disease	1	1	1	1
Coagulopathy		1	1	
Congestive heart failure	1	1	1	1
Deficiency anaemias			1	
Dementia	1	1	1	1
Depression				
Diabetes with chronic complications				
Diabetes without complications				
Hemiplegia/paraplegia		1	1	
Hypertension complicated				
Hypertension uncomplicated				
Hypothyroidism				
Metastatic solid tumor	1	1	1	1
Mild liver disease			1	
Moderate or severe liver disease			1	
Myocardial infarction	1	1	1	1
Obesity				
Peptic ulcer disease	1			
Peripheral vascular disease		1	1	
Psychoses				
Pulmonary circulation disorders				
Renal disease including renal failure	1	1	1	1
Rheumatic disease including some other connective tissue disorders				
Valvular disease				
Maximum total comorbidity score	9	12	15	8

5 Injury comorbidity indices for burden outcomes

This chapter includes a manuscript submitted (in January 2020) to *Injury*

(currently under review)

titled

"Australian Injury Comorbidity Indices (AICIs) to predict burden and readmission among hospital-admitted injury patients".

(attached at the end of the chapter)

The conclusions drawn in the previous chapters (3 & 4), along with recommendations from past research, is that the associations between comorbidity and outcomes vary depending on the outcome and the population. This implies that when comorbidity indices are derived for *burden outcomes*, their relevance to the outcome must be considered.

The most widely used comorbidity index, the CCI, was derived for predicting 1-year mortality, while the next most popular index, the ECM, was derived for predicting in-hospital death, LOS and hospital-costs among general medical patient populations. Due to a lack of outcome-specific measures, these existing indices are currently applied for any outcome in clinical and research settings, regardless of the true association between the comorbidity and the outcome. Further, due to the absence of patient-group specific measures, these same indices are applied in most 'injury' settings. The aim of this chapter was to derive indices that capture the association between comorbidity and burden and readmission outcomes for injury populations. The outcomes of interest are overnight stay, LOS for those staying overnight, hospital costs (direct + indirect), and 30-day-, all-cause and non-planned readmissions. The

new indices were then compared with the existing indices, and both the new and existing indices were validated in population subgroups and on interstate data from NSW and WA.

The research questions answered in this chapter are similar to the previous chapter, except, in the last chapter, the questions were answered using mortality outcomes, while in this chapter they are answered using burden outcomes.

1. Based on the analysis of Victorian data:

    a. How can comorbidity best be quantified?

    b. Does an updated comorbidity index perform significantly better than the CCI, updated CCI by Quan et al. and the ECM in predicting injury outcomes?

    c. Do the indices' performance (predictive ability) vary among subgroups of the population?

2. Do the indices developed on Victorian data effectively capture the effect of comorbidity on injury outcomes in other Australian states?

5.1 Summary

Overall, the baseline models used for predicting overnight stay and readmissions contributed between 60-70% of the predictive power (based on the AUC statistics). The R^2 for the baseline factors for LOS and costs were 8% and 31% respectively. Adding comorbidity did not substantially improve prediction. The number and type of comorbidities associated with outcomes varied based on the outcome, as was seen in the previous chapter for mortality.

Five new binary indices for overnight stay, LOS, costs and 30-day all-cause and non-planned readmissions (AICI-os, AICI-los, AICI-cost, AICI-acr and AICI-npr) were derived. Two parsimonious binary indices were also derived: one for *burden* (AICI-b) and another (AICI-r) for readmission outcomes. All burden- and readmission-related indices were different to the mortality indices derived in the previous chapter.

A *binary* representation of comorbidities was found to be similar in terms of predictive abilities to a weighted comorbidity index. The number of associated comorbidities, and their effect sizes were different to the associations established with the CCI and ECM. The new indices performed equally well to the lengthy ECM and in certain instances outperformed the CCI. This answered questions 1a and 1b: how can comorbidity best be quantified and do the new indices perform better than the CCI and ECM (in terms of burden outcomes)?

To answer question 1c: do the indices' performance (predictive ability) vary among subgroups of the population (in terms of burden outcomes); the validation of all new and existing indices in subgroups varied depending on the outcome *and* the subgroup. Their validations returned similar results in some instances while in others, the AICIs and ECM outperformed the CCI.

It was found that the AICI-los was robust for use in NSW and WA, and AICI-acr and -npr robust for use in WA alone. To answer question 2; in terms of burden-related comorbidity indices, not all indices (new or existing) were equally robust across states; further work is required to understand the underlying dynamics within interstate populations, hospital facilities, comorbidity capture and the outcomes themselves.

5.2 Implications

The new burden-related indices allow for a more appropriate quantification of the effect of each comorbidity on outcomes, as they include conditions with statistically significant relationships to the outcomes. They also use current data as opposed to using existing indices that are based on historical data, making them more relevant.

However, the internal validations and tests of robustness in other states proved that the performances of all new and existing indices varied with the outcome and the group of patients they were applied to. Therefore, caution must be exercised when applying the new or existing indices as they may tend to favour specific population groups.

Quite importantly, socio-demographics, injury characteristics and comorbidity alone did not sufficiently account for the variability in outcomes, implying that further investigation into other variables likely to affect burden outcomes must be explored in future.

The empirical comorbidity weights derived in this study for each outcome are different to those weights allocated by the CCI. This once again implies that the effect of a comorbidity weighs differently based on the population, outcome, and may require periodic review. The associations established between comorbidities and burden outcomes in this chapter are different to those established for mortality outcomes in the previous chapter. The next chapter focuses on establishing the associations between complications-related outcomes and comorbidities.

MONASH University

Tara Fernando <tara.fernando@monash.edu>

A manuscript number has been assigned - JINJ-D-20-00045

1 message

Injury <eesserver@eesmail.elsevier.com> 9 January 2020 at 01:44
Reply-To: Injury <injury@elsevier.com>
To: tara.fernando@monash.edu, tharanga361@gmail.com

*** Automated email sent by the system ***

Dear Ms. Fernando

Thank you for submitting your manuscript entitled "Australian Injury Comorbidity Indices (AICIs) to predict burden and readmission among hospital-admitted injury patients". It has been assigned the following manuscript number: JINJ-D-20-00045 and is now being handled by one of the Editors.

Two or more peer reviewers will be invited and encouraged to complete their review as quickly as possible. Once two or more completed reviews have been received, the Editor will make an initial decision and you will then be informed accordingly.

You will be able to check on the progress of your manuscript by logging on to EES as an author. The URL is https://ees.elsevier.com/jinj/

Thank you for submitting your work to Injury.

Best regards

Injury

Australian Injury Comorbidity Indices (AICIs) to predict burden and readmission among hospital-admitted injury patients

Dasamal Tharanga Fernando[a], B.Sc.(Hons)

[a] Corresponding author
[b] Monash University Accident Research Centre
Monash University, Clayton Campus
21 Alliance Lane,
Clayton,
Victoria, Australia
Email:tara.fernando@monash.edu
Phone: +61-3-9905 1805

Janneke Berecki-Gisolf, Ph.D
Associate Professor, Monash University Accident Research Centre[b]
Director, Victorian Injury Surveillance Unit
Email:janneke.berecki-gisolf@monash.edu

Stuart Newstead, B.Sc. (Hons), M.Sc., Ph.D., A.Stat
Associate Professor and Deputy Director, Monash University Accident Research Centre[b]
Email: Stuart.Newstead@monash.edu

Zahid Ansari, MPh, MS, Ph.D
Clinical Associate Professor,
Victorian Agency for Health Information
50 Lonsdale Street
Melbourne, Victoria 3000
Email: Zahid.Ansari@vahi.vic.gov.au

Australian Injury Comorbidity Indices (AICIs) to predict burden and readmission among hospital-admitted injury patients

Keywords: burden, comorbidity, index, injury

Abstract

Objective

Existing comorbidity measures predict mortality among general patient populations. Due to the lack of outcome specific and patient-group specific measures, the existing indices are also applied to non-mortality outcomes in injury epidemiology. This study derived indices to capture the association between comorbidity, and burden and readmission outcomes for injury populations.

Research Design

Injury-related hospital admissions data from July 2012 to June 2014 (161,334 patients) for the state of Victoria, Australia were analyzed. Various multivariable regression models were run and results used to derive both binary and weighted indices that quantify the association between comorbidities and length of stay (LOS), hospital costs and readmissions. The new and existing indices were validated internally among patient subgroups, and externally using data from the states of New South Wales and Western Australia.

Results

Twenty-four comorbidities were significantly associated with overnight stay, twenty-seven with LOS, twenty-eight with costs, ten with all-cause and eleven with non-planned 30-day readmissions. The number of and types of comorbidities, and their relative impact were different to the associations established with the existing Charlson Comorbidity Index (CCI) and Elixhauser Comorbidity Measure (ECM). The new indices performed equally well to the long-listed ECM and in certain instances outperformed the CCI.

Conclusions

The more parsimonious, up to date, outcome and patient-specific indices presented in this study are better suited for use in present injury epidemiology. Their use can be trialed by hospital administrations in resource allocation models and patient classification models in clinical settings.

1 Introduction

1.1 Background

Hospital-admitted injury patients can experience adverse outcomes during the course of the hospital stay, and comorbidities have the potential to increase that burden. Adverse outcomes include complications, extended hospital stay, readmission to hospital, discharge to long-term nursing care facilities and death. Previous research shows that among hospitalised patients, burden-related outcomes such as readmission to hospital [1-3], length of stay in hospital (LOS) [4, 5] and hospital costs [6-8] are associated with comorbidity. Therefore, comorbidities can *increase the likelihood* of adverse events occurring, and among injury patients, comorbidities may worsen their outcomes. The ability to quantify the effect of comorbidities for injury patients can assist in predicting outcomes in clinical settings and estimating injury burden in epidemiological research.

Currently there are several established methods for quantifying the association between comorbidities and outcomes. These include capturing the presence of at least one, each or a count of all comorbidities, and the use of comorbidity indices such as the Charlson Comorbidity Index (CCI) [9] and the Elixhauser Comorbidity Measure (ECM) [10]. The CCI allocates a weighted summed score for seventeen comorbid conditions while the ECM is a binary representation of thirty conditions. The CCI was originally derived in 1987 to assess the effect of comorbidity on mortality and is one of the most widely used. It was last updated in 2011 by Quan et al. [11]. The ECM was enhanced by van Walraven et al. in 2009 into a total score [12] and is less popular than the CCI. Some research considered the ECM as inconvenient due to the high number of comorbidities, arguing this may result in over-fitting [13].

Factors associated with outcomes for injury patients are different to those for general hospital-admitted patients [10, 13, 14]. Comorbidity measures should therefore consider the study

population as well as the outcome. The type of data available, disease prevalence and clinical relevance also play an important role when deriving such measures. Reflecting this, using existing indices such as the CCI (derived for mortality) does not work well for other burden outcomes [6, 14].

1.2 Study aims

The purpose of this study was: (1) to derive and validate new indices to establish the association between comorbidity and readmission and burden-related outcomes, such as LOS and hospital costs, among hospital-admitted injury patients using Australian administrative datasets; and (2) to compare the performance of the new indices with the CCI and ECM.

2 Materials and Methods

2.1 Data sources

An analysis of existing morbidity data from the states of Victoria (Victorian Admitted Episodes Dataset (VAED)), New South Wales (NSW) (Admitted Patient Data Collection (APDC)) and Western Australia (WA) (Hospital Morbidity Data Collection (HMDC)) was carried out. The Victorian dataset was used for deriving injury comorbidity indices and the interstate datasets were used for external validation. Data provision and linkage were undertaken by the Centre for Victorian Data Linkage (CVDL) in Victoria, the Centre for Health Record Linkage (CHeReL) in NSW and the Data Linkage Branch (DLB) in WA.

These datasets capture all public and private hospital admissions, and contain patient demographics and morbidity information. The morbidity information includes forty diagnosis fields for Victoria, fifty-one for NSW and seventy-eight for WA, consisting of disease, injury and external cause data, coded to the ICD Tenth Revision, Australian Modifications (ICD-10-AM) [15]. Mortality data were extracted from (i) the Registrar of Births, Deaths and Marriages

(RBDM) in NSW and (ii) Mortality Register in WA. Direct and indirect hospital costs for Victoria was sourced from the Victorian Cost Data Collection (VCDC) by CVDL and linked to the VAED.

2.2 Data linkage

Data linkage (using patient-specific identifiers) was performed by CVDL using deterministic data linkage for the Victorian data while CHeReL used probabilistic matching techniques for NSW, and DLB in WA used a multi-faceted process which includes numerous automated and manual sub-processes. CVDL estimates the false positive rate to be between 0.5% to 1%, and the false negative match rates to be between 1% - 2% [16] and CHeReL estimates the false positives to be around 0.5% [17]. It is expected that the false negatives in the Western Australian Data Linkage System (WADLS) exceed the number of false positives, estimates for which are not attempted by the linkage unit [18].

2.3 Case selection

Injury cases were identified and selected as those with records containing an ICD-10-AM diagnosis code in the range "S00" to "T75" or "T79" in the first appearing diagnosis field in the morbidity datasets; a practice commonly used for national reporting [19]. Case selection was further limited to index injury (i.e., the first injury record in the morbidity dataset for a patient during the study period) and residents belonging to each state. Consecutive records of inward transfers from other hospitals or statistical separations within the same hospital were considered to be part of one episode. Children less than 15 years of age were excluded when deriving the indices and validating; the rational being that children differ to the rest of the cohort in terms of comorbidity prevalence.

The Victorian cohort

The comorbidity indices derivation cohort consisted of adult patients with an index injury admission between 01 July 2012 and 30 June 2014 (140,094 patients). They were followed up over a period of two years for subsequent hospital admissions.

The NSW and WA cohorts

The same selection process was used as for the Victorian cohort using the APDC (201,791 patients) and HMDC (71,771 patients). These patients were also followed up in the mortality data to identify patients for censoring; those who died within 30 days of hospital-discharge did not have a possibility for readmission and were excluded from analysis pertaining to readmissions within 30 days [20, 21].

2.4 Coding of outcomes, factors and comorbidities

2.4.1 Outcomes

Two outcomes related to LOS, one cost outcome and two outcomes related to readmissions were chosen for index derivation, some details of which has been published before [22].

The LOS days in the morbidity datasets were re-coded as (1) a binary code "0" for those who were discharged on the same day and "1" for those who stayed overnight, and (2) the number of days in hospital as a continuous variable for the index episode for those who stayed at least overnight. Case selection for the second LOS outcome was limited to those who stayed less than 1 month in the index episode (92% of cases).

Hospital costs were recorded in Australian dollars (AUD), and were available for Victoria for July 2012 to June 2015 only for those admitted to public hospitals. Costs were standardized to 2012 dollar values using the Australian Consumer Price Index [23]. Due to its skewness it was log transformed for analysis.

Two forms of readmissions (any-cause and non-planned) were coded, both with a binary outcome: "1" for patients readmitted within 30 days and "0" otherwise, limited to the first occurring readmission. Patients who died in hospital and those who left against medical advice were excluded.

2.4.2 Factors

The factors considered were age, gender, body-region, injury type, injury severity, SEIFA (Socio Economic Indexes For Areas), country of birth, geographic region and comorbidity. The coding is similar to that used in a previous study (Fernando et al., in press) [24].

2.4.3 Comorbidities

A combination of the CCI [9] and ECM [10] comorbidity groups per Quan et al. (2011) [25] and Sundararajan et al. [26] were used to select the list of comorbidities for study. Further details can be found in Fernando et al. (in press) [24].

2.5 Statistical analysis

A negative binomial regression model for LOS, a linear regression model for log transformed costs and a logistic regression model for the binary outcomes (overnight stay, all-cause- and non-planned 30-day readmission) were fitted using multivariable regression. Socio-demographic variables and injury characteristics were entered in the baseline models.

Predictive power of the logistic regression models was assessed using discrimination (area under the receiver operating characteristic curve - ROC) and classification tables. The area under the curve (AUC) ranges from 0 to 1, with a value of under 0.7 representing poor discrimination and anything above that as good discrimination. Classification tables were derived on the basis of using a classification cut-off probability that maximized the combined sensitivity and specificity of the table based on the ROC. The adjusted R^2 and McFadden's R^2 was used to determine predictive ability for the linear and negative binomial models.

After running the baseline models, comorbidity was added in various forms. Models were compared using the Akaike Information Criterion (AIC) [27]. Using a backward elimination process starting with all thirty-one conditions in the model fitted as binary variables, a final model was derived which excludes comorbidities that no longer improve the model and were hence eliminated by the process.

A weighted comorbidity index was derived using the final binary model, weights were computed for each comorbid condition using the following: resulting odds ratios (ORs) for each condition from logistic regression, incident rate ratios (IRRs) for the negative binomial regression; and the exponential of the beta coefficients for the linear regression model. The following rules were applied in allocating weights: the condition was dropped from the index if the weight<1.2; 1.2≤ weight <1.5 resulted in a score of 1; 1.5≤ weight <2.5=2; 2.5≤ weight <3.5=3 and so on. These weights were summed up to create the summed weighted score.

Two more indices were also derived: one parsimonious binary injury comorbidity index for burden and one for readmissions. The first was created using only conditions that were associated with LOS and cost, while the second was based on conditions associated with readmissions.

Finally, a validation of the newly derived indices was carried out. The indices were internally validated on patient subgroups and externally on NSW and WA datasets. The validation models were the same baseline model identified for each outcome in Victoria with the addition of the binary index, the weighted index, the burden index, the readmission index, CCI, updated CCI and ECM to represent comorbidity. The models with various indices were assessed for predictive ability using the AUC and classification tables and adjusted R^2s. Stata 14.0 (StataCorp) was used to analyze the data [28].

3 Results

3.1 Overview of the Victorian study population

Nearly a third (30.9%) of the population were 65 years and above, 55.3% were males and approximately 13% had serious injuries. More than half (59.6%) of the patients had a main injury to the extremities and the highest proportion of injuries were fractures (41.3%) (Table 1).

The median LOS was 1 day (IQR 1-3) for the entire cohort while those with at least one comorbidity had a higher median LOS of 4 days (IQR 1-17). Over two-thirds required an overnight stay (68.4%). The mean hospital cost was AUD 7457.3 (95% CI 7,370.1 -7,544.5) (based on 123,207 episodes of care with complete cost data), while the mean cost for those with at least one comorbidity was nearly double (AUD 14,157.5 (95% CI 13,876.8 - 14,438.2)). Excluding patients who died or left against medical advice, 11.4% had at least one any-cause and 7.6% one non-planned readmission to a hospital within 30 days of being discharged for the index admission. These readmissions increased to 18% and 12.7% respectively for those with at least one comorbidity. Overall, comorbidity increased with age, was higher among females, and higher among patients with serious-injuries.

Table 1- Characteristics of the Victorian, NSW and WA study populations

3.2 Comorbidity in the Victorian study population (adults)

Alcohol dependence, cardiac arrhythmia, dementia, depression, diabetes, hypertension without complications and renal disease were the most commonly recorded comorbidities among injured adults (>15 year of age) (Table 2). The comorbidities associated with a high burden on the system (LOS and costs) were not the same comorbidities that were associated with high readmission rates.

Table 2- Presence of comorbidity and the association with burden and readmission outcomes (Victoria, age 15 years and over)

3.3 Multivariable regression modelling

3.3.1 Baseline models

Results for the baseline models are presented in Table 3 (model *i*). The baseline factors differ for each outcome (see stepwise breakdown of factor inclusion in appendix table A2). Age, gender and injury characteristics all improved the model fit for all baseline models except for all-cause readmissions, where adding gender and injury severity did not improve the model fit any further. However, gender was retained in all baseline models for consistency. Patients from regional areas were more likely to stay overnight vs patients from metropolitan areas. The baseline model for costs is similar to overnight stay which is expected given costs are highly correlated to LOS. Region of residence was associated with readmissions.

The AUC of 0.75 for non-same day discharge implies good predictive ability by the factor variables while the AUCs for readmission of 0.61-0.62 indicates relatively poorer predictive power by these variables alone (Table 3). The adjusted R^2 statistic for cost indicates that 31% of the variability is explained by the fitted factors while the corresponding adjusted R^2 for LOS for those who stayed overnight was 8%.

Table 3- Performance of selected comorbidity measures in assessing the association between comorbidity and selected outcome measures (Victoria)

3.3.2 Fitting comorbidity using various measures

Models *ii-vii* are baseline models with comorbidity fitted using the newly derived binary (*ii*) and weighted comorbidity indices (*iii*), existing indices (CCI (*iv*), updated CCI (*v*) and ECM (*vi*)) and the parsimonious indices (conditions common to burden/readmission outcomes alone) (*vii*) (Table 3). Results from fitting comorbidity using *other* forms are also presented

in an appendix (Table A2). The model coefficients and weights for each comorbidity, by outcome is presented in Table 4.

3.3.3 Interaction effects

Interaction effects between age and sex, comorbidities and age, and comorbidities and sex, were also modelled. The age and sex selection was because of their known interaction with disease [29], while the comorbidity related interactions were selected due to the expectation that the severity and impact of comorbidity can vary with age and sex. The interaction terms improved model fit but provided very little or no improvement to the predictive ability of the models, and were therefore dropped from the analysis. Plots representing interaction effects are included in Appendix A2.

Table 4: Risk adjusted odds ratios, incident rate ratios, beta-coefficients and suggested weights

3.3.4 Overnight stay

The best fit model, as indicated by the lowest AICs; was model *vi* (containing the ECM), followed by model *ii* (containing the Australian Injury Comorbidity Index for overnight stay (AICI-os) with twenty-four comorbidities). The CCI (model *iv*) and updated CCI (model *v*) had much poorer fit.

Comparing predictive abilities using the AUC and false negative rates (FNs) (Table 5), the AICI-os and the ECM performed best; an FN in this instance is when a patient with overnight stay is incorrectly classified as discharged on the same day. The AUCs were very similar for AICI-os and ECM; model with ECM (0.761(CI 0.759-0.764)) and model with AICI-os (0.760 (CI 0.757-0.763)). The predictive ability of the CCI and updated CCI were weaker (AUCs of 0.752 (CI 0.749-0.754) and 0.752 (CI 0.749-0.754) respectively) than the aforementioned indices. There was no significant difference at the 5% level between the FN rates of the AICI-os (30.3) and the ECM (30.2), while the FN rate of the CCI (31.1) was significantly

higher. Therefore, the AICI-os with twenty-four comorbidities performs better than the CCI, performs equally to the ECM with the added advantage that it uses fewer comorbidities than the ECM.

Table 5: False negative rates for various indices by outcome in population groups

3.3.5 LOS (overnight stay patients)

Fit of the various models from best to worst was observed in the following order; ECM, followed by the Australian Injury Comorbidity Index for LOS (AICI-los) with twenty-seven comorbidities while the CCI and updated CCI had poorer fit. In terms of predictive ability (using the highest adjusted R^2), the models containing the ECM (8.9%) and the AICI-los (8.8%) were higher than the CCI (8.3%) and updated CCI (8.2%), but the differences were relatively small. Based solely on model fit, the new index fits better than the CCI. The AICI-los does not fit as well as the ECM but the trade-off lies in modelling thirty conditions in the ECM as opposed to only twenty-seven in the AICI-los.

3.3.6 Cost

The best fit was once again seen in models with the ECM, followed by the Australian Injury Comorbidity Index for costs (AICI-cost) with twenty-eight comorbidities while the CCI and updated CCI had a poorer fit. Predictive power in terms of the adjusted R^2 was best in the model with the ECM (36.6%), followed by AICI-cost (35.9%), while predictive powers of the CCI (32.8%) and updated CCI (32.5%) were lower. Similar to the AICI-los, the AICI-cost fits better than the CCI and less so than the ECM. Once again, the trade-off between the AICI-cost and the ECM is the number of conditions.

3.3.7 All-cause 30-day readmission

In terms of model fit, the best were models with the ECM, followed by the Australian Injury Comorbidity Index for all-cause 30-day readmissions (AICI-acr) with ten comorbidities, while once again the CCI and updated CCI had a poorer fit. The AUC for all models for this

outcome was close to but less than 0.7, indicating that the power of the models was somewhat poor and could probably be improved by factors not already adjusted for. There was no significant difference in predictive ability (based on AUC) between the model containing the AICI-acr (AUC 0.625 (CI 0.621-0.630)), the ECM (AUC 0.626 (CI 0.622-0.631), CCI (AUC 0.622 (CI 0.617-0.626)) or updated CCI (AUC 0.620 (CI 0.615-0.624)). There was no statistically significant difference between the models with AICI-acr (41%), CCI (41%) or ECM (40.7%) with regard to FN rates. The AICI-acr exhibits similar capacity as the existing indices except that it includes fewer conditions than the CCI and ECM.

3.3.8 Non-planned 30-day readmissions

The best fit was again observed for models with the ECM, followed by the Australian Injury Comorbidity Index for non-planed 30-day readmissions (AICI-npr) with eleven comorbidities poorer fit for the CCI and updated CCI (75174). Again, there were no significant differences between the AUC statistics for all the models including the AICI-npr (AUC 0.637 (CI 0.632-0.642)), the ECM (AUC 0.639 (CI 0.634-0.644)), the CCI (AUC 0.633 (CI 0.628-0.638) and updated CCI (AUC 0.631 (CI 0.626-0.637)); the CIs overlapped. There were also no significant differences between the FN rates for the models with the AICI-npr (39.8%), CCI (40.6%) and ECM (39.8%). Similar to all-cause readmissions, the AICI-npr has the advantage of having fewer conditions than the CCI and ECM.

3.3.9 Parsimonious indices

A binary index (model *vii*) (Table 3) with twenty-three conditions common in the LOS and cost indices (Australian Injury Comorbidity Index for burden (AICI-b)) and one with eight conditions common to readmissions (Australian Injury Comorbidity Index for readmissions (AICI-r)) was also derived (see appendix table A7 for conditions included). Overall, comparing the AUCs, FNs and R^2s showed the parsimonious indices can be used for

predicting the corresponding outcomes without much loss in predictive capacities (Table 3 and Table 5).

3.4 Comparison of conditions included in new and existing indices

Table 4 shows the corresponding weights for each comorbidity by outcome for the AICIs, CCI, Quan update to CCI and van Walraven update to ECM weights. Conditions like HIV/AIDS, cerebrovascular disease, dementia, metastatic solid tumors, myocardial infarction and pulmonary circulation disorders are allocated weights in the existing indices, while for some of the outcomes, they show no association in the new indices.

3.5 Internal and external validations

The newly derived indices along with the CCI and ECM were validated in subgroups of the Victorian population. The groups were children (<15 years), adults (>=65 years), males, females, adults with non-severe injuries, adults with intracranial injuries, adults with blunt trauma, adults with penetrating injuries and hip fracture patients aged 45 years and over. A detailed discussion of results can be found in Appendix A3 while model results are presented in appendix table A4 and FNs in Table 5. The new indices and the ECM validated better than the CCI in general across most subgroups for burden outcomes. For readmission outcomes, there was no difference in predictive powers across new and existing indices, the only difference being that the ECM had significantly lower FNs among older adults, females and blunt trauma patients.

External validations were carried out on the entire adult portion of the interstate cohorts. Comorbidity prevalence for these are presented in Appendix Table A5. An explanation of the validation analysis can be found in Appendix A3 with model results in Appendix Table A6 and FN rates in Table 5. For overnight stay, all indices validated well; NSW a little better than WA and the new indices and ECM better than the CCI, but no significant differences in

FN rates. For LOS, WA had higher R^2s than Victoria and NSW, and the ECM performed best followed by the AICI and the CCI. For readmissions, AUCs were low (poor predictive power) for all indices and not significantly different, nor were the FN rates. WA data overall had better predictive power than the other two states.

Suggestions on how the indices can be used are provided in Appendix A4. A summary table of conditions included in the AICIs, CCI and ECM are presented in Table A7.

4 Discussion

4.1 Main findings

The number and type of comorbidities associated with outcomes vary based on the outcome. The AICIs provide up-to-date, injury and outcome specific parsimonious indices that perform equally well to the long-listed ECM, and in most instances outperforms the widely used CCI.

4.2 Study strengths

This study shows that pre-existing comorbidities associated with burden and readmission outcomes for injury patients are different for each outcome enforcing the need for outcome-specific indices. For instance, conditions associated with LOS and costs were somewhat similar (though not identical) while conditions associated with readmissions were similar but far fewer in number than burden outcomes. The CCI and ECM has been cited extensively (CCI 29,383 citations and ECM 5,450 citations according to Google Scholar as of October 2019) but are often applied to injury populations and non-mortality outcomes when they were originally derived for predicting mortality [30].

The fact that the association between comorbidities and outcomes vary and that the CCI performed better for predicting mortality than LOS and readmissions has been shown in other

studies [14, 31]. Both a previous study (Fernando et al., in press) [24] and the present study gave the same findings for the CCI, ECM and the AICIs.

The new indices allow a more appropriate quantification of the effect of each comorbidity on the outcomes as opposed to using existing indices that are based on older data. More specifically; conditions like HIV/AIDS and metastasis contain the highest risk scores according to the CCI, but the results from this study shows that these conditions have much smaller or no effect on burden and readmission outcomes. Myocardial infarction allocates a certain element of risk in the CCI, but according to the findings here, it only impacted the prediction of costs. Peptic ulcer disease is also allocated a risk element in the CCI but shows association only with LOS and cost and has no association with readmissions in the present study.

A study by Moor et al. (2008) further showed that the CCI weights assigned to conditions did not correspond to their study coefficients when assessing mortality for trauma patients [32] which the present study also confirmed. Moor et al. (2008) recommended three steps to creating appropriate empirical weights; 1) use a large representative database, 2) use appropriate generalizable trauma populations and 3) be up-to-date, all of which the present study has encompassed.

A number of studies in the past have indicated the need for study-specific comorbidity indices or weights [31, 33-36]. This study has shown the validity of those recommendations by deriving new indices and comparing their performance and parsimoniousness against the existing general indices. The characteristics of the populations, hospital facilities and comorbidity prevalence drive the outcomes.

The only study that derived a comorbidity index for injury populations was by Thompson et al. (2010) which derived the Mortality Risk Score for Trauma (MoRT) using six

comorbidities. The predictive power of their index was identical to the CCI and did not show any improvement whereas the indices derived in this study performed a little better.

Another strength of this study is the extensive validations of the new and existing indices carried out in subgroups and external populations. It was seen that in most instances the ECM performed best followed by the AICIs and CCI in predicting outcomes. However, the trade-off on the number of comorbidities modelled and the relevance to the outcome could be the deciding point for whether the ECM or AICI is used.

The new indices may be more versatile for use than the Multipurpose Australian Comorbidity Scoring System (MACSS) which was derived by Holman et al. (2005) [31]. The MACSS was not considered for evaluation in this study because it includes: (i) 102 comorbidities (far less parsimonious than all other indices), (ii) conditions like tuberculosis and (iii) certain symptoms and late effects which are not chronic diseases.

Moor et.al. (2008) [32] and Toson et al. (2015) [14] both claimed that a binary representation of comorbidities was sufficient for establishing the association between comorbidities and outcomes for injury patients and this study has validated that claim. Farley et al. (2005) [6] found that costs were better predicted by a count of comorbidities over the CCI; this study found that the binary representation had more predictive power than the count of comorbidities. The difference could be due to the fact that they used diagnosis clusters which we have not investigated in this study.

4.3 Study limitations

4.3.1 Data limitations

The < 0.7 AUC statistics for assessing readmissions indicate that additional variables are required to explain these outcomes. Readmissions could be due to injuries, comorbidities,

complications and health service delivery. Adjusting for the cause of readmission, which was not available in these datasets, may help improve the baseline model.

LOS and costs could also be largely driven by hospital facilities as well as the medical and surgical procedures carried out. The distance from a patient's residence to the hospital could be another important factor, all of which was not part of the data included in this study. LOS can also be dependent on the total patient turnout at a hospital; hospitals with low resources may tend to discharge patients sooner resulting in lower LOS, likewise they could result in higher numbers of readmissions. Accounting for these in the baseline models may improve predictive abilities, but not necessarily the comorbidity indices.

4.3.2 Comorbidity capture

4.3.2.1 Drawback of using administrative data

The administrative data used in this study does not capture the severity of comorbidities. It may also not capture all comorbidities as the function of most administrative datasets is for informing hospital reimbursement, therefore commodities that are not actively treated within the episode may not be indicated.

4.3.2.2 Lookback periods

The inclusion of lookback periods could improve comorbidity capture. However, the new indices are meant for use at the point of hospital admission, and data for lookback periods are generally unavailable at that point; therefore, inclusion of these will be useful only during research and not in clinical settings.

4.3.3 Practical application

Care should be exercised when using the new indices in populations where the injury profile or the prevalence of comorbidity are different, as was seen in the subgroup analysis (Appendix A3). Further, they should probably not be used to compare the performance of

specific hospitals as the driving factors of hospital performance likely vary largely on type, size and location of hospitals.

4.4 Implications

Epidemiological research and resource use predictions for hospital admitted injury patients will benefit from using the AICIs that have been specifically derived and validated for this group of patients. For example, they can be used by hospitals for planning beds, and by health service administrators when budgeting for future hospital expenditure for injury patients with comorbidities.

Another advantage of such indices is that they are less resource intensive given they use information available at point of hospital admission. Clinicians can estimate LOS and the possibility of readmissions for injury patients, adjusting for the effect of comorbidities, and plan the services required accordingly. These indices do not replace clinical knowledge when deciding hospital logistics required for treating patients but maybe used in assisting with the decision-making processes.

4.5 Future research

The AICIs can be further validated in other countries to understand if additional adjustments are required to make them more robust. Another step forward for these indices will be to incorporate comorbidity severity measures, which may improve the indices' abilities.

5 Conclusion

Comorbidities associated with burden and readmission outcomes vary with the outcome and the method used to measure the outcome. The up-to-date, injury- and outcome-specific AICIs for burden and readmissions, which are similar to the binary index such as the ECM but with fewer conditions, are sufficient for predicting outcomes and does not warrant weighted

indices such as the CCI. The AICIs could be further improved by adding more information on comorbidities.

6 References

1. Moore L, Stelfox HT, Turgeon AF, et al. Rates, Patterns, and Determinants of Unplanned Readmission After Traumatic Injury: A Multicenter Cohort Study. *Ann. Surg.* 2014;259:374-380.
2. Morris DS, Rohrbach J, Sundaram LMT, et al. Early hospital readmission in the trauma population: Are the risk factors different? *Injury.* 2014;45:56-60.
3. Librero J, Peiró S, Ordiñana R. Chronic comorbidity and outcomes of hospital care: length of stay, mortality, and readmission at 30 and 365 days. *J. Clin. Epidemiol.* 1999;52:171-179.
4. Kuwabara K, Matsuda S, Imanaka Y, et al. Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database. *J Trauma Acute Care.* 2010;68:463-470.
5. Bochicchio GV, Joshi M, Bochicchio K, Shih D, Meyer W, Scalea TM. Incidence and impact of risk factors in critically ill trauma patients. *World J. Surg.* 2006;30:114-118.
6. Farley JF, Harley CR, Devine JW. A Comparison of Comorbidity Measurements to Control for Confounding in Health Outcomes Studies. Minneapolis: University of Minnesota; 2005.
7. Johansson PA, Farup PG, Bracco A, Vandvik PO. How does comorbidity affect cost of health care in patients with irritable bowel syndrome? A cohort study in general practice. *BMC Gastroenterol.* 2010;10:31.
8. Mackenzie JE, Rivara PF, Jurkovich JG, et al. The National Study on Costs and Outcomes of Trauma. *J Trauma.* 2007;63:S54-S67.

9. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J. Chronic Dis.* 1987;40:373-383.

10. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. *Med. Care.* 1998;36:8-27.

11. Quan H, Li B, Couris CM, et al. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. *Am. J. Epidemiol.* 2011;173:676-682.

12. van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data. *Med. Care.* 2009:626-633.

13. Yurkovich M, Avina-Zubieta JA, Thomas J, Gorenchtein M, Lacaille D. A systematic review identifies valid comorbidity indices derived from administrative health data. *J. Clin. Epidemiol.* 2015;68:3-14.

14. Toson B, Harvey LA, Close JC. The ICD-10 Charlson Comorbidity Index predicted mortality but not resource utilization following hip fracture. *J. Clin. Epidemiol.* 2015;68:44-51.

15. Australian Consortium for Classification Development. The international statistical classification of diseases and related health problems, tenth revision, australian modification (ICD-10-AM/ACHI/ACS) (Tenth ed.). Darlinghurst, NSW: Independent Hospital Pricing Authority; 2012.

16. Centre for Victorian Data Linkage. Data Linkage ResultsPersonal communication.

17. Centre for Health Record Linkage. Master linkage key quality assurance report2012:CheReL website.

18. Department of Health. Data linkage – making the right connections Western Australia: Government of Western Australia - Department of Health; 2016.

19. AIHW:Pointer SC. Trends in hospitalised injury, Australia, 1999–00 to 2010–11. *Injury research and statistics series no. 86. Cat. no. INJCAT 162.* Canberra: AIHW; 2013.

20. Mitchell RJ, Curtis K, Braithwaite J. Health outcomes and costs for injured young people hospitalised with and without chronic health conditions. *Injury.* 2017;48:1776-1783.

21. Bureau of Health Information. *Return to acute care following hospitalisation : spotlight on readmissions.* Chatswood, New South Wales: NSW Bureau of Health Information; 2015.

22. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study. *BMC Public Health.* 2019;19:798.

23. Australian Bureau of Statistics. 6401.0 Consumer Price Index, Australia. Vol 2018: Australian Bureau of Statistics; 2018:ABS website.

24. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. The Australian Injury Comorbidity Index (AICI) to predict mortality. *Ann. Emerg. Med.* (in press).

25. Quan H, Sundararajan V, Halfon P, et al. Coding Algorithms for Defining Comorbidities in ICD-9-CM and ICD-10 Administrative Data. *Med. Care.* 2005;43:1130-1139.

26. Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. *J. Clin. Epidemiol.* 2004;57:1288-1294.

27. Akaike H. A new look at the statistical model identification. *IEEE Trans Automat Contr.* 1974;19:716-723.

28. StataCorp. Stata Statistical Software: Release 14: College Station, TX: StataCorp LP; 2015.

29. Vlassoff C. Gender differences in determinants and consequences of health and illness. *J. Health Popul. Nutr.* 2007;25:47-61.

30. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. Effect of comorbidity on injury outcomes: a review of existing indices. *Ann. Epidemiol.* 2019;36:5-14.

31. Holman CAJ, Preen DB, Baynham NJ, Finn JC, Semmens JB. A multipurpose comorbidity scoring system performed better than the Charlson index. *J. Clin. Epidemiol.* 2005;58:1006-1014.

32. Moore L, Lavoie A, Sage NL, et al. Using Information on Preexisting Conditions to Predict Mortality From Traumatic Injury. *Ann. Emerg. Med.* 2008;52:356-364.e352.

33. Ghali WA, Hall RE, Rosen AK, Ash AS, Moskowitz MA. Searching for an improved clinical comorbidity index for use with ICD-9-CM administrative data. *J. Clin. Epidemiol.* 1996;49:273-278.

34. Klabunde CN, Potosky AL, Legler JM, Warren JL. Development of a comorbidity index using physician claims data. *J. Clin. Epidemiol.* 2000;53:1258-1267.

35. Martins M, Blais R. Evaluation of comorbidity indices for inpatient mortality prediction models. *J. Clin. Epidemiol.* 2006;59:665-669.

36. Schneeweiss S, Wang PS, Avorn J, Glynn RJ. Improved comorbidity adjustment for predicting mortality in Medicare populations. *Health Serv. Res.* 2003;38:1103-1120.

Conflict of Interest Statement
Click here to download Conflict of Interest Statement: Conflict of interest statement.docx

Conflict of interest statement

The authors declare that they have no competing interests, financially or otherwise.

Acknowledgements
Click here to download Acknowledgements: Acknowledgements.docx

Acknowledgements: The authors would like to thank the Centre for Victorian Data Linkage, the Centre Health Record Linkage in New South Wales and the Western Australian Data Linkage Branch and the custodians of data collections for providing linkage services and the data, and Prof. James Harrison at the National Injury Surveillance Unit for providing the survival risk ratios.

Other relevant information

Click here to download Supplementary Materials: Other relevant information.docx

Highlights
Click here to download Highlights: Highlights.docx

Highlights

1. The number and types of comorbidities associated with burden outcomes for injury patients, and their relative impact, varies with the outcome.
2. The injury comorbidity indices performed equally well, and in certain instances outperformed the existing indices.
3. The parsimonious, up to date, outcome and patient-specific indices will better inform future injury epidemiology research.

Manuscript tables
Click here to download Table: Manuscript tables.docx

Table 1: Characteristics of the Victorian, NSW and WA study populations

	Patients admitted[1] between July 2012 and June 2014, n (%)											
	Victoria				NSW				WA			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients			161334				233521				84877	
Age group (years)												
0-14 years	21240	13.2	1.4	0.01 (0.01-0.02)	31730	13.6	1.5	0.02 (0.01-0.02)	13106	15.4	1.9	0.02 (0.02-0.02)
15-24 years	23213	14.4	9.9	0.12 (0.11-0.12)	33888	14.5	11.0	0.13 (0.13-0.14)	13676	16.1	15.3	0.18 (0.17-0.19)
25-44 years	36262	22.5	13.0	0.16 (0.16-0.17)	51737	22.2	13.5	0.17 (0.17-0.18)	22617	26.6	18.6	0.23 (0.22-0.23)
45-64 years	30799	19.1	19.3	0.25 (0.25-0.26)	44501	19.1	18.3	0.25 (0.24-0.26)	16344	19.3	21.6	0.29 (0.28-0.30)
65-84 years	31390	19.5	35.9	0.54 (0.53-0.54)	44948	19.2	33.2	0.51 (0.50-0.52)	12598	14.8	36.0	0.55 (0.54-0.57)
85 and over	18430	11.4	40.0	0.62 (0.60-0.63)	26717	11.4	38.2	0.60 (0.59-0.62)	6536	7.7	41.5	0.64 (0.62-0.66)
Gender												
Male[2]	89144	55.3	16.8	0.24 (0.23-0.24)	131598	56.4	16.2	0.23 (0.23-0.24)	49994	58.9	18.0	0.24 (0.24-0.25)
Female	72190	44.7	23.5	0.33 (0.33-0.34)	101923	43.6	22.7	0.33 (0.32-0.33)	34883	41.1	24.0	0.33 (0.32-0.34)
Injury severity[3]												
Serious injury (ICISS<0.941)	20884	12.9	40.6	0.64 (0.63-0.65)	30265	13.0	35.5	0.57 (0.56-0.59)	9566	11.3	38.3	0.60 (0.58-0.62)
Other injury (ICISS>=0.941)	140450	87.1	16.7	0.22 (0.22-0.23)	203256	87.0	16.6	0.23 (0.23-0.23)	75311	88.7	18.2	0.24 (0.23-0.24)
Grouped body region												

Head/face/neck	32052	19.9	19.2	0.26 (0.25-0.27)	48159	20.6	20.7	0.29 (0.28-0.29)	18350	21.6	23.7	0.31 (0.30-0.32)
Trunk	20730	12.8	25.0	0.36 (0.35-0.37)	29199	12.5	23.1	0.34 (0.33-0.35)	9835	11.6	23.5	0.34 (0.33-0.35)
Upper extremity	54549	33.8	9.8	0.12 (0.12-0.13)	77389	33.1	9.4	0.12 (0.12-0.13)	27833	32.8	10.9	0.14 (0.13-0.14)
Lower extremity	41528	25.7	22.8	0.34 (0.33-0.35)	57954	24.8	19.6	0.30 (0.30-0.31)	20678	24.4	20.9	0.31 (0.30-0.32)
Multiple body regions	53	0.0	18.9	0.25 (0.09-0.40)	170	0.1	18.8	0.26 (0.17-0.35)	51	0.1	25.5	0.31 (0.15-0.47)
Unspecified body region	585	0.4	22.6	0.31 (0.26-0.37)	1247	0.5	22.3	0.34 (0.30-0.38)	376	0.4	22.1	0.30 (0.23-0.36)
Body region not relevant	11837	7.3	47.7	0.66 (0.65-0.68)	19403	8.3	45.5	0.65 (0.64-0.66)	7754	9.1	41.6	0.56 (0.55-0.58)
Grouped injury type (First occurring)												
Superficial injury	8055	5.0	23.8	0.34 (0.32-0.35)	14875	6.4	22.6	0.33 (0.32-0.34)	4659	5.5	27.7	0.37 (0.35-0.39)
Open wound	22398	13.9	14.8	0.19 (0.18-0.20)	35691	15.3	16.9	0.23 (0.22-0.23)	12623	14.9	20.6	0.27 (0.26-0.28)
Fracture	66686	41.3	19.6	0.29 (0.28-0.29)	94258	40.4	17.3	0.26 (0.26-0.27)	30714	36.2	18.5	0.27 (0.26-0.27)
Dislocation, sprain & strain	10989	6.8	8.2	0.10 (0.10-0.11)	13330	5.7	6.6	0.09 (0.08-0.09)	6755	8.0	7.5	0.09 (0.08-0.10)
Injury to nerves & spinal cord	2038	1.3	10.4	0.13 (0.11-0.14)	2559	1.1	8.6	0.11 (0.10-0.13)	1147	1.4	11.1	0.14 (0.11-0.16)
Injury to blood vessels	1347	0.8	11.5	0.15 (0.12-0.17)	1096	0.5	15.0	0.19 (0.16-0.22)	650	0.8	18.5	0.23 (0.19-0.28)
Injury to muscle & tendon	8451	5.2	9.1	0.11 (0.10-0.12)	10921	4.7	6.7	0.08 (0.08-0.09)	5423	6.4	10.1	0.12 (0.11-0.13)
Crushing injury	335	0.2	3.3	0.04 (0.01-0.06)	469	0.2	3.4	0.04 (0.02-0.06)	166	0.2	4.2	0.05 (0.01-0.08)
Traumatic amputation	1612	1.0	7.3	0.08 (0.07-0.10)	1622	0.7	6.8	0.08 (0.06-0.10)	747	0.9	7.9	0.09 (0.07-0.11)
Eye injury-excluding foreign body	512	0.3	16.4	0.22 (0.17-0.27)	919	0.4	17.3	0.22 (0.19-0.26)	308	0.4	19.5	0.23 (0.17-0.28)

Intracranial injury	6416	4.0	29.4	0.43 (0.41-0.45)	9355	4.0	28.1	0.42 (0.41-0.44)	3385	4.0	30.6	0.44 (0.41-0.47)
Injury to internal organs	1762	1.1	23.5	0.32 (0.29-0.35)	2198	0.9	22.5	0.32 (0.29-0.35)	1066	1.3	23.7	0.34 (0.29-0.38)
Foreign body	2733	1.7	11.3	0.15 (0.13-0.16)	3947	1.7	9.2	0.12 (0.10-0.13)	1486	1.8	9.6	0.12 (0.10-0.14)
Burns	1879	1.2	15.1	0.21 (0.18-0.23)	3244	1.4	8.8	0.12 (0.10-0.14)	1660	2.0	14.3	0.20 (0.17-0.22)
Other and unspecified injury	14284	8.9	19.8	0.27 (0.26-0.28)	19634	8.4	19.6	0.28 (0.27-0.29)	6334	7.5	22.8	0.30 (0.29-0.32)
Systemic-poisoning/toxic effects	10536	6.5	49.5	0.68 (0.67-0.70)	17162	7.3	47.8	0.67 (0.66-0.68)	6866	8.1	43.5	0.59 (0.57-0.60)
Other effects of external cause/complication	1301	0.8	32.5	0.54 (0.48-0.59)	2241	1.0	28.2	0.47 (0.43-0.50)	888	1.0	26.7	0.40 (0.35-0.45)
Geographic region												
Metropolitan Area	118959	73.7	19.8	0.28 (0.27-0.28)	158595	67.9	18.9	0.28 (0.27-0.28)	60151	70.9	19.7	0.27 (0.27-0.28)
Rural Area	42375	26.3	19.8	0.28 (0.27-0.29)	74918	32.1	19.2	0.27 (0.26-0.27)	24405	28.8	22.1	0.29 (0.28-0.30)
Unknown					8	0.0	*	0.25 (-0.07-0.57)	321	0.4	34.6	0.42 (0.35-0.50)
All-cause readmissions[4]	17946	11.4	18.0	0.46 (0.45-0.47)	30922	13.7	25.1	0.38 (0.37-0.39)	9930	12.1	30.6	0.45 (0.43-0.47)
Non-planned readmissions[4]	11954	7.6	12.7	0.50 (0.48-0.51)	17362	7.7	30.8	0.47 (0.46-0.49)	6130	7.5	36.1	0.53 (0.51-0.55)
LOS (median, IQR)	1 (1-3)		4 (1-17)	0.28 (0.27-0.28)	1 (1-4)		4 (1-15)	0.27 (0.27-0.28)	1 (1-3)		2 (1-10)	0.28 (0.27-0.28)
Overnight stay	110337	68.4	24.7	0.36 (0.35-0.36)	165056	70.7	23.3	0.34 (0.34-0.35)	58886	69.4	22.9	0.33 (0.32-0.33)
Cost (mean, 95% CI)[5]	7457.3 (7370.1-7544.5)				14157.5 (13876.8-14438.2)							

Notes:

1. Index injury admissions to all public and private hospitals, limited to residents within the relevant state
2. Intersex/intermediate/unstated sex patient counts less than 5 added to the majority sex group to protect confidentiality

3. Worst injury method-ICD-based Injury Severity Score less than or equal to 0.941 considered as serious injury
4. Based on 157866 patients for Victoria, 225047 for NSW and 82212 for WA (excludes patients who died or left against medical advice)
5. Based on 123207 patients with complete cost data

Table 2: Presence of comorbidity and the association with burden and readmission outcomes (Victoria, age 15 years and over)

Comorbidity	Index admission LOS (n=140094)				Index hospital admission cost (n=104609)	
	n (%)	Index LOS (mean, 95% CI)	Adjusted OR[#1] (95% CI)	IRR[##2] (95% CI)	Cost[###] (mean, 95% CI)	Adjusted beta coefficient[#] (95% CI)
HIV/AIDS	54 (0.0)	11.1 (5.0-17.1)	1.05 (0.53-2.11)	1.11 (0.85-1.44)	13064.9 (6672.5-19457.4)	0.40 (0.12-0.68)
Alcohol dependence	6425 (4.6)	7.1 (6.6-7.6)	1.38 (1.29-1.48)	1.17 (1.14-1.20)	8927.3 (8464.9-9389.7)	0.20 (0.17-0.23)
Drug dependence	1496 (1.1)	8.1 (7.0-9.2)	2.34 (2.01-2.72)	1.56 (1.49-1.64)	11228.8 (10195.1-12262.4)	0.47 (0.41-0.52)
Any malignancy	706 (0.5)	21.2 (19.5-22.8)	6.15 (3.09-12.22)	1.56 (1.40-1.73)	23110.8 (21132.8-25088.8)	0.65 (0.52-0.78)
Blood loss anemia	170 (0.1)	24.7 (21.0-28.5)	5.56 (1.71-18.08)	1.40 (1.20-1.63)	29192.2 (24390.9-33993.4)	0.61 (0.44-0.77)
Cardiac arrhythmias	3775 (2.7)	19.0 (18.2-19.8)	2.44 (2.14-2.79)	1.32 (1.28-1.36)	20572.8 (19549.5-21596.0)	0.48 (0.44-0.51)
Cerebrovascular disease	602 (0.4)	24.2 (21.0-27.5)	1.74 (1.08-2.79)	1.18 (1.08-1.29)	23691.7 (21388.4-25995.0)	0.19 (0.08-0.30)
Chronic pulmonary disease	1302 (0.9)	22.8 (21.3-24.2)	6.24 (4.22-9.22)	1.46 (1.38-1.54)	26770.7 (24643.6-28897.8)	0.57 (0.51-0.64)
Coagulopathy	1133 (0.8)	18.9 (17.1-20.8)	3.73 (2.79-4.98)	1.43 (1.35-1.51)	22255.5 (19748.4-24762.6)	0.49 (0.43-0.56)
Congestive heart failure	1257 (0.9)	24.8 (23.5-26.2)	6.84 (4.14-11.30)	1.27 (1.20-1.34)	26944.0 (25240.2-28647.9)	0.38 (0.31-0.44)
Deficiency anemias	578 (0.4)	24.1 (21.9-26.2)	8.56 (4.65-15.75)	1.62 (1.50-1.76)	22380.0 (20429.5-24330.5)	0.66 (0.56-0.75)
Dementia	2889 (2.1)	16.2 (15.5-16.9)	1.99 (1.70-2.34)	1.05 (1.02-1.09)	16671.0 (15968.2-17373.8)	0.16 (0.11-0.20)
Depression	2966 (2.1)	9.2 (8.6-9.9)	3.25 (2.89-3.65)	1.93 (1.86-2.01)	10987.7 (10125.5-11849.9)	0.63 (0.59-0.67)
Diabetes with chronic complications	4243 (3.0)	18.6 (17.9-19.4)	1.42 (1.26-1.60)	1.27 (1.23-1.31)	19104.6 (18238.8-19970.5)	0.26 (0.22-0.30)
Diabetes without complications	8969 (6.4)	12.0 (11.5-12.4)	1.20 (1.13-1.28)	1.12 (1.09-1.14)	12223.6 (11710.2-12737.0)	0.10 (0.07-0.12)
Hemiplegia/paraplegia	538 (0.4)	25.7 (22.3-29.1)	4.14 (2.51-6.83)	1.61 (1.47-1.78)	25975.1 (22961.5-28988.6)	0.60 (0.49-0.71)
Hypertension complicated	54 (0.0)	25.4 (17.6-33.1)	O	1.41 (1.09-1.82)	28041.4 (20243.3-35839.6)	0.48 (0.20-0.76)
Hypertension uncomplicated	4510 (3.2)	21.5 (20.7-22.2)	2.45 (2.11-2.84)	1.26 (1.22-1.30)	22582.5 (21702.8-23462.3)	0.41 (0.37-0.45)

Hypothyroidism	152 (0.1)	21.3 (17.3-25.3)	21.00 (2.89-152.81)	1.72 (1.48-1.99)	22116.8 (17862.1-26371.5)	0.56 (0.38-0.74)
Metastatic solid tumor	380 (0.3)	20.4 (18.3-22.5)	1.39 (0.54-3.57)	1.32 (1.15-1.52)	22163.4 (19616.7-24710.1)	0.16 (-0.02-0.33)
Mild liver disease	1167 (0.8)	10.5 (9.4-11.7)	1.63 (1.37-1.93)	1.27 (1.20-1.34)	13166.4 (11933.4-14399.4)	0.31 (0.25-0.38)
Moderate or severe liver disease	116 (0.1)	20.2 (15.1-25.3)	20.59 (2.83-149.95)	1.83 (1.54-2.19)	25608.6 (19508.8-31708.4)	0.81 (0.60-1.01)
Myocardial infarction	248 (0.2)	23.9 (21.0-26.8)	2.78 (1.11-6.96)	0.96 (0.85-1.09)	27805.7 (24266.1-31345.4)	0.24 (0.10-0.38)
Obesity	229 (0.2)	27.9 (22.6-33.2)	4.39 (2.26-8.54)	2.10 (1.85-2.39)	29539.4 (23323.0-35755.7)	0.80 (0.65-0.95)
Peptic ulcer disease	84 (0.1)	20.3 (14.4-26.2)	1.96 (0.90-4.29)	1.55 (1.25-1.92)	23885.5 (15681.1-32089.8)	0.66 (0.40-0.91)
Peripheral vascular disease	702 (0.5)	17.2 (15.4-19.1)	3.10 (2.34-4.11)	1.88 (1.76-2.02)	19444.2 (17341.6-21546.9)	0.75 (0.66-0.83)
Psychoses	568 (0.4)	20.2 (17.2-23.1)	5.54 (3.96-7.74)	3.14 (2.91-3.39)	22213.8 (19103.3-25324.3)	1.04 (0.95-1.13)
Pulmonary circulation disorders	133 (0.1)	33.6 (28.0-39.2)	9.06 (1.24-66.43)	1.81 (1.52-2.16)	39206.1 (30612.7-47799.5)	0.79 (0.58-0.99)
Renal disease including renal failure	3402 (2.4)	22.3 (21.5-23.2)	1.54 (1.29-1.84)	1.16 (1.11-1.20)	22865.3 (21879.6-23851.0)	0.20 (0.15-0.24)
Rheumatic disease including some other connective tissue disorders	177 (0.1)	25.4 (21.7-29.1)	31.75 (4.41-228.88)	1.93 (1.66-2.23)	27277.3 (22034.9-32519.7)	0.84 (0.66-1.02)
Valvular disease	326 (0.2)	27.9 (24.8-31.0)	5.23 (2.27-12.02)	1.36 (1.22-1.52)	28473.9 (24958.1-31989.7)	0.41 (0.28-0.55)

Notes:
#Adjusted with baseline model - see Table 3 footnotes for baseline model details
##Patients with same day separations (n=40819) excluded from the 140094 (adult patients) (n=99275)
Based on patients with complete cost data
1. Outcome=at least one overnight stay
2. Outcome=LOS for those who had at least one overnight stay but <= 30 days (n=8472 patients excluded from 99275)

Table 2 continued.....

Comorbidity	Readmissions (n=136670)				
	n (%)	All-cause 30-day readmission		Non-planned 30-day readmission	
	beta coefficient# (95% CI)	% with condition that had the outcome	Adjusted OR# (95% CI)	% with condition that had the outcome	Adjusted OR# (95% CI)
HIV/AIDS	53 (0.0)	20.8	1.50 (0.76-2.95)	20.8	2.57 (1.31-5.06)
Alcohol dependence	6119 (4.5)	15.3	1.22 (1.13-1.31)	11.4	1.34 (1.23-1.46)
Drug dependence	1350 (1.0)	16.0	1.27 (1.09-1.48)	12.9	1.45 (1.23-1.72)
Any malignancy	561 (0.4)	44.0	3.45 (2.71-4.40)	20.7	1.64 (1.21-2.23)
Blood loss anemia	159 (0.1)	22.0	1.20 (0.81-1.77)	14.5	1.09 (0.69-1.72)
Cardiac arrhythmias	3480 (2.5)	18.2	1.06 (0.97-1.16)	13.4	1.10 (0.99-1.22)
Cerebrovascular disease	545 (0.4)	19.1	1.08 (0.83-1.40)	14.3	1.08 (0.81-1.45)
Chronic pulmonary disease	1176 (0.9)	23.0	1.40 (1.21-1.61)	18.2	1.60 (1.37-1.86)
Coagulopathy	1032 (0.8)	23.5	1.43 (1.23-1.66)	18.1	1.53 (1.30-1.81)
Congestive heart failure	1048 (0.8)	24.0	1.20 (1.03-1.40)	19.3	1.34 (1.14-1.58)
Deficiency anemias	550 (0.4)	24.0	1.28 (1.05-1.58)	18.7	1.42 (1.13-1.77)
Dementia	2663 (1.9)	15.5	0.89 (0.79-0.99)	13.3	1.12 (1.00-1.26)
Depression	2877 (2.1)	18.8	1.36 (1.23-1.52)	11.8	1.14 (1.01-1.30)
Diabetes with chronic complications	3978 (2.9)	23.9	1.24 (1.13-1.35)	16.9	1.29 (1.16-1.43)
Diabetes without complications	8655 (6.3)	17.2	1.18 (1.11-1.25)	12.1	1.21 (1.13-1.30)
Hemiplegia/paraplegia	494 (0.4)	18.6	1.17 (0.89-1.54)	13.8	1.20 (0.88-1.63)
Hypertension complicated	42 (0.0)	40.5	1.89 (1.01-3.55)	21.4	1.30 (0.61-2.76)
Hypertension uncomplicated	4165 (3.0)	22.0	1.05 (0.96-1.15)	16.0	1.13 (1.02-1.25)
Hypothyroidism	148 (0.1)	17.6	0.93 (0.61-1.44)	14.9	1.15 (0.73-1.83)
Metastatic solid tumor	287 (0.2)	46.3	1.37 (0.98-1.92)	22.6	1.50 (0.99-2.26)
Mild liver disease	1055 (0.8)	21.5	1.65 (1.41-1.93)	17.3	1.84 (1.55-2.18)

Moderate or severe liver disease	90 (0.1)	30.0	1.45 (0.90-2.32)	23.3	1.41 (0.84-2.36)
Myocardial infarction	197 (0.1)	21.8	1.08 (0.76-1.53)	18.3	1.21 (0.83-1.76)
Obesity	219 (0.2)	20.1	1.34 (0.95-1.89)	16.4	1.59 (1.10-2.31)
Peptic ulcer disease	70 (0.1)	17.1	0.96 (0.51-1.82)	7.1	0.54 (0.21-1.36)
Peripheral vascular disease	673 (0.5)	19.5	1.37 (1.12-1.67)	12.9	1.30 (1.03-1.64)
Psychoses	536 (0.4)	21.6	1.64 (1.33-2.03)	15.1	1.56 (1.22-1.99)
Pulmonary circulation disorders	120 (0.1)	20.8	0.94 (0.59-1.49)	15.0	0.89 (0.53-1.51)
Renal disease including renal failure	3042 (2.2)	30.0	1.92 (1.73-2.12)	20.2	1.56 (1.39-1.76)
Rheumatic disease including some other connective tissue disorders	168 (0.1)	22.0	1.39 (0.95-2.02)	15.5	1.46 (0.95-2.24)
Valvular disease	290 (0.2)	19.3	1.03 (0.76-1.39)	14.5	1.08 (0.77-1.51)

Notes:
#Adjusted with baseline model - see Table 3 footnotes for baseline model details

Table 3: Performance of selected comorbidity measures in assessing the association between comorbidity and selected outcome measures (Victoria)

Model	LOS[1.1]		LOS[1.2]		Hospital costs [2]	
	AUC (95% CI)	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC	Adjusted R^2	Model fit AIC
(i) Baseline model	0.748 (0.745-0.750)	145468	0.080	579331	0.312	304799
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.760 (0.757-0.763)	142523	0.088	572274	0.359	297352
(iii) Baseline model + selected comorbidities (modelled as a weighted summed score)[3]	0.760 (0.757-0.762)	142582	0.088	572673	0.357	297674
(iv) Baseline model + comorbidity using CCI weights	0.752 (0.749-0.754)	144554	0.083	577080	0.328	302263
(v) Baseline model + comorbidity using Quan weights	0.752 (0.749-0.754)	144527	0.082	577610	0.325	302663
(vi) Baseline model + ECM	0.761 (0.759-0.764)	142174	0.089	571537	0.366	296207
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.760 (0.757-0.762)	142603	0.088	448263	0.358	297494

Notes:

1.1 Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)

1.2 Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges with 1-30 days stay (negative binomial model)

2. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth; outcome= hospital costs (Ln transformed linear model)

3. See Methods for weight calculation, excludes weights resulting from an OR<1.2

See Table 4 for selected comorbidities for each outcome

Table 3 continued…

Model	All-cause 30-day readmission[1]		Non-planned 30-day readmission[2]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
(i) Baseline model	0.611 (0.606-0.615)	99275	0.623 (0.618-0.628)	75455
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.625 (0.621-0.630)	98445	0.637 (0.632-0.642)	74950
(iii) Baseline model + selected comorbidities (modelled as a weighted summed score)[3]	0.625 (0.620-0.629)	98473	0.636 (0.631-0.642)	74946
(iv) Baseline model + comorbidity using CCI weights	0.622 (0.617-0.626)	98662	0.633 (0.628-0.638)	75096
(v) Baseline model + comorbidity using Quan weights	0.620 (0.615-0.624)	98824	0.631 (0.626-0.637)	75174
(vi) Baseline model + ECM	0.626 (0.622-0.631)	98457	0.639 (0.634-0.644)	74912
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.622 (0.617-0.626)	98707	0.635 (0.630-0.640)	75010

Notes:

1. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all cause 30-day readmission (logistic model)
2. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30 day readmission (logistic model)
3. See Methods for weight calculation, excludes weights resulting from an OR<1.2

See Table 4 for selected comorbidities for each outcome

Table 4: Risk adjusted odds ratios, incident rate ratios, beta-coefficients and suggested weights

	Australian Injury Comorbidity Indices				Existing comorbidity indices		
	LOS		LOS		CCI	Updated CCI per Quan et al. (2011)	ECM point scores per van Walraven et al. (2009)
	OR (95% CI)	Injury comorbidity index weight	IRR (95% CI)	Injury comorbidity index weight			
15-24 years	0.43 (0.41-0.45)		0.41 (0.40-0.42)				
25-44 years	0.48 (0.46-0.50)		0.45 (0.45-0.46)				

45-64 years	0.63 (0.60-0.66)		0.57 (0.56-0.58)				
65-84 years	Reference group		Reference group				
85+ years	1.16 (1.09-1.22)		1.26 (1.24-1.29)				
Female gender	1.11 (1.08-1.14)		1.12 (1.11-1.13)				
Serious injury	4.92 (4.56-5.32)		1.83 (1.80-1.86)				
HIV/AIDS	-	-	-	-	6	4	0
Alcohol dependence	1.38 (1.29-1.48)	1	1.17 (1.14-1.20)*	-	#	#	0
Drug dependence	2.34 (2.01-2.72)	2	1.56 (1.49-1.64)	2	#	#	-7
Any malignancy	7.39 (4.52-12.08)	7	1.56 (1.40-1.73)	2	2	2	4
Blood loss anemia	5.98 (1.84-19.37)	6	1.40 (1.20-1.63)	1	#	#	-2
Cardiac arrhythmias	2.45 (2.15-2.80)	2	1.32 (1.28-1.36)	1	#	#	5
Cerebrovascular disease	-	-	1.18 (1.08-1.29)*	-	1	0	##
Chronic pulmonary disease	6.29 (4.26-9.30)	6	1.46 (1.38-1.54)	1	1	1	3
Coagulopathy	3.74 (2.80-4.99)	4	1.43 (1.35-1.51)	1	#	#	3
Congestive heart failure	7.06 (4.27-11.67)	7	1.27 (1.20-1.34)	1	1	2	7
Deficiency anemias	8.70 (4.73-16.00)	9	1.62 (1.50-1.76)	2	#	#	-2
Dementia	2.00 (1.70-2.34)	2	-	-	1	2	##
Depression	3.25 (2.89-3.65)	3	1.93 (1.86-2.01)	2	#	#	-3
Diabetes with chronic complications	1.42 (1.26-1.60)	1	1.27 (1.23-1.31)	1	2	1	0
Diabetes without complications	1.20 (1.13-1.28)	1	1.12 (1.09-1.14)	-	1	0	0
Hemiplegia/paraplegia	5.03 (3.12-8.10)	5	1.62 (1.47-1.78)	2	2	2	7
Hypertension complicated	-	-	-	-	#	#	0
Hypertension uncomplicated	2.49 (2.15-2.88)	2	1.25 (1.21-1.29)	1	#	#	0
Hypothyroidism	21.25 (2.92-154.54)	21	1.72 (1.49-2.00)	2	#	#	0
Metastatic solid tumor	-	-	1.32 (1.15-1.51)	1	6	6	12
Mild liver disease	1.63 (1.38-1.93)	2	1.27 (1.20-1.34)	1	1	2	11
Moderate or severe liver disease	20.78 (2.85-151.33)	21	1.83 (1.53-2.19)	2	3	4	11

Myocardial infarction	-	-	-	-	1	0	##
Obesity	4.41 (2.27-8.56)	4	2.10 (1.85-2.39)	2	#	#	-4
Peptic ulcer disease	-	-	1.55 (1.25-1.91)	2	1	0	0
Peripheral vascular disease	3.11 (2.35-4.13)	3	1.88 (1.76-2.02)	2	1	0	2
Psychoses	5.54 (3.96-7.74)	6	3.14 (2.91-3.40)	3	#	#	0
Pulmonary circulation disorders	-	-	1.81 (1.52-2.15)	2	#	#	4
Renal disease including renal failure	1.58 (1.32-1.89)	2	1.17 (1.12-1.21)*	-	2	1	5
Rheumatic disease including some other connective tissue disorders	33.10 (4.59-238.47)	33	1.93 (1.67-2.24)	2	1	1	0
Valvular disease	5.28 (2.30-12.13)	5	1.36 (1.22-1.52)	1	#	#	-1

Note:
- Condition not significantly associated with outcome
Not included in CCI list
Not included in ECM list
*Excluded from weighted index as OR<1.2

Table 4 continued....

	Australian Injury Comorbidity Indices						Existing comorbidity indices		
	Hospital cost		All-cause 30-day readmission		Non-planned 30-day readmission		CCI	Updated CCI per Quan et al. (2011)	ECM point scores per van Walraven et al. (2009)
	Beta coefficient (95% CI)	Injury comorbidity index weight[1]	OR (95% CI)	Injury comorbidity index weight	OR (95% CI)	Injury comorbidity index weight			
15-24 years	-0.25 (-0.28--0.23)		0.47 (0.44-0.50)		0.51 (0.47-0.55)				
25-44 years	-0.21 (-0.23--0.19)		0.58 (0.55-0.61)		0.64 (0.60-0.68)				
45-64 years	-0.16 (-0.18--0.14)		0.70 (0.67-0.74)		0.69 (0.65-0.73)				
65-84 years	Reference group		Reference group		Reference group				
85+ years	0.02 (0.00-0.04)		1.01 (0.96-1.06)		1.18 (1.12-1.26)				

Female gender	-0.03 (-0.04--0.01)		0.97 (0.94-1.01)		0.95 (0.91-0.99)				
serious injury	0.89 (0.86-0.91)		-		1.07 (1.00-1.14)				
HIV/AIDS	-	-	-	-	-	-	6	4	0
Alcohol dependence	0.20 (0.17-0.23)	1	1.23 (1.14-1.33)	1	1.35 (1.24-1.47)	1	#	#	0
Drug dependence	0.47 (0.41-0.52)	2	-	-	1.46 (1.23-1.72)	1	#	#	-7
Any malignancy	0.74 (0.65-0.83)	2	4.10 (3.45-4.86)	4	-	-	2	2	4
Blood loss anemia	0.61 (0.45-0.78)	2	-	-	-	-	#	#	-2
Cardiac arrhythmias	0.48 (0.44-0.52)	2	-	-	-	-	#	#	5
Cerebrovascular disease	-	-	-	-	-	-	1	0	##
Chronic pulmonary disease	0.57 (0.51-0.64)	2	1.45 (1.26-1.67)	1	1.63 (1.40-1.90)	2	1	1	3
Coagulopathy	0.49 (0.43-0.56)	2	1.48 (1.27-1.72)	1	1.60 (1.36-1.88)	2	#	#	3
Congestive heart failure	0.38 (0.31-0.45)	1	-	-	1.40 (1.19-1.65)	1	1	2	7
Deficiency anemias	0.66 (0.56-0.75)	2	-	-	-	-	#	#	-2
Dementia	0.16 (0.11-0.20)*	-	-	-	-	-	1	2	##
Depression	0.63 (0.59-0.67)	2	1.38 (1.24-1.53)	1	-	-	#	#	-3
Diabetes with chronic complications	0.26 (0.22-0.30)	1	1.26 (1.15-1.38)	1	1.33 (1.20-1.47)	1	2	1	0
Diabetes without complications	0.10 (0.07-0.12)*	-	1.18 (1.11-1.26)*	-	1.22 (1.14-1.31)	1	1	0	0
Hemiplegia/paraplegia	0.70 (0.60-0.79)	2	-	-	-	-	2	2	7
Hypertension complicated	0.48 (0.20-0.76)	2	-	-	-	-	#	#	0
Hypertension uncomplicated	0.42 (0.38-0.46)	2	-	-	-	-	#	#	0
Hypothyroidism	0.56 (0.39-0.74)	2	-	-	-	-	#	#	0
Metastatic solid tumor	-	-	-	-	2.42 (1.83-3.21)	2	6	6	12
Mild liver disease	0.32 (0.25-0.38)	1	1.74 (1.50-2.03)	2	1.89 (1.60-2.24)	2	1	2	11
Moderate or severe liver disease	0.81 (0.60-1.01)	2	-	-	-	-	3	4	11

Myocardial infarction	0.24 (0.10-0.38)	1	-	-	-	-	1	0	##
Obesity	0.80 (0.65-0.95)	2	-	-	-	-	#	#	-4
Peptic ulcer disease	0.65 (0.40-0.91)	2	-	-	-	-	1	0	0
Peripheral vascular disease	0.75 (0.66-0.83)	2	-	-	-	-	1	0	2
Psychoses	1.04 (0.95-1.13)	3	1.69 (1.36-2.08)	2	1.57 (1.23-2.00)	2	#	#	0
Pulmonary circulation disorders	0.79 (0.58-0.99)	2	-	-	-	-	#	#	4
Renal disease including renal failure	0.19 (0.14-0.24)	1	2.02 (1.83-2.21)	2	1.67 (1.50-1.86)	2	2	1	5
Rheumatic disease including some other connective tissue disorders	0.83 (0.66-1.01)	2	-	-	-	-	1	1	0
Valvular disease	0.41 (0.28-0.55)	2	-	-	-	-	#	#	-1

Note:
- Condition not significantly associated with outcome
Not included in CCI list
Not included in ECM list
*Excluded from weighted index as OR<1.2
1. Weight=exp(beta)

Table 5: False negative rates for various indices by outcome in population groups

Outcome	Number of patients in initial cohort	Number (%) of patients with outcome	Number (%) of patients classified as not having the outcome when likely to have using the;			
			outcome-specific binary index	parsimonious index	CCI	ECM
			Adults (>=15 years) - all injuries			
At least one overnight stay	140094	99275 (70.9)	30093/99273 (30.3)	30059/99273 (30.3)	30868/99273 (31.1)	30008/99219 (30.2)
All-cause 30-day readmission	136670	16672 (12.2)	6833/16672 (41.0)	6803/16672 (40.8)	6828/16672 (41.0)	6790/16672 (40.7)

Non-planned 30-day readmission	136670	11150 (8.2)	4440/11150 (39.8)	4449/11150 (39.9)	4527/11150 (40.6)	4437/11150 (39.8)
Children (<15 years) - all injuries						
At least one overnight stay	21240	11062 (52.1)	3537/21194 (32.1)	3537/21194 (32.1)	3829/21238 (34.6)	3827/21189 (34.8)
All-cause 30-day readmission	21196	1274 (6.0)	486/21179 (38.2)	487/21179 (38.2)	491/21183 (38.5)	474/21141 (37.2)
Non-planned 30-day readmission	21196	804 (3.8)	303/21046 (37.7)	303/21056 (37.7)	303/21101 (37.7)	343/21006 (42.7)
Patients 65 years and above						
At least one overnight stay	49820	41600 (83.5)	11092/49525 (26.9)	11163/49525 (27.0)	11806/49820 (28.4)	11097/49480 (26.9)
All-cause 30-day readmission	47968	7948 (16.6)	3589/47968 (45.2)	3546/47968 (44.6)	3609/47968 (45.4)	3484 /47961 (43.8)
Non-planned 30-day readmission	47968	5424 (11.3)	2378/47968 (43.8)	2373/47968 (43.8)	2381/47968 (43.9)	2287/47961 (42.2)
Adult males						
At least one overnight stay	76211	51046 (67.0)	16312/76109 (32.0)	16336/76109 (32.1)	16670/76210 (32.7)	16334/76034 (32.1)
All-cause 30-day readmission	74206	8359 (11.3)	3280/74205 (39.2)	3304/74205 (39.5)	3272/74205 (39.1)	3262/74205 (39.0)
Non-planned 30-day readmission	74206	5626 (7.6)	2157/74205 (38.3)	2133/74205 (37.9)	2143/74205 (38.1)	2088/74205 (37.1)
Adult females						
At least one overnight stay	63883	48229 (75.5)	14205/63702 (29.6)	14187/63702 (29.5)	14594/63882 (30.3)	14138/63675 (29.4)
All-cause 30-day readmission	62464	8313 (13.3)	3623/62463 (43.6)	3602/62463 (43.3)	3588/62463 (43.2)	3570/62459 (42.9)
Non-planned 30-day readmission	62464	5524 (8.8)	2351/62463 (42.6)	2292/62463 (41.5)	2346/62463 (42.5)	2301/62459 (41.7)
Adults with non-severe injuries						
At least one overnight stay	119916	79942 (66.7)	26684/119915 (33.4)	26885/119915 (33.6)	27455/119915 (34.3)	26672/119889 (33.4)
All-cause 30-day readmission[1]						
Non-planned 30-day readmission	117951	9030 (7.7)	3560/117950 (39.4)	3553/117950 (39.4)	3639/117950 (40.3)	3570/117950 (39.5)

Adults with intracranial injury[2]						
At least one overnight stay	5456	4093 (75.0)	883/5190 (23.1)	886/5190 (23.2)	915/5456 (22.4)	882/5136 (23.4)
All-cause 30-day readmission	5026	633 (12.6)	235/5026 (37.1)	237/5026 (37.4)	236/5026 (37.3)	231/5026 (36.5)
Non-planned 30-day readmission	5026	492 (9.8)	184/5026 (37.4)	180/5026 (36.6)	181/5026 (36.8)	188/5018 (38.2)
Patients with hip fractures 45 years and above[3]						
At least one overnight stay	161334	110337 (68.4)	36536/161332 (33.1)	36714/161332 (33.3)	37331/161332 (33.8)	36497/161277 (33.1)
All-cause 30-day readmission	7400	1115 (15.1)	452/7400 (40.5)	519/7400 (46.6)	491/7400 (44.0)	464/7394 (41.6)
Non-planned 30-day readmission	7400	818 (11.1)	382/7400 (46.7)	393/7400 (48.0)	306/7400 (37.4)	344/7394 (42.1)
Adults with blunt trauma[4]						
At least one overnight stay	94698	71004 (75.0)	19844/94629 (28.0)	19924/94629 (28.1)	20331/94696 (28.6)	19973/94545 (28.2)
All-cause 30-day readmission	92217	12169 (13.2)	5174/92204 (42.5)	5210/92204 (42.8)	5201/92204 (42.7)	5069/ 92204 (41.7)
Non-planned 30-day readmission	92217	8313 (9.0)	3441/92204 (41.4)	3423/92204 (41.2)	3451/92204 (41.5)	3380/92177 (40.7)
Adults with penetrating trauma[5]						
At least one overnight stay	13313	7937 (59.6)	3165/13262 (40.1)	3161/13262 (40.1)	3245/13313 (40.9)	3143/13256 (39.9)
All-cause 30-day readmission	13075	1058 (8.1)	460/13071 (43.5)	466/13071 (44.1)	461/13071 (43.6)	456/13045 (43.2)
Non-planned 30-day readmission	13075	651 (5.0)	270/13058 (41.5)	270/13059 (41.5)	291/13059 (44.7)	275/13017 (42.2)
NSW validation (age>=15 years)						
At least one overnight stay	201791	146177 (72.4)	46323/146176 (31.7)	46336/146176 (31.7)	46670/146176 (31.9)	46102/146176 (31.5)
All-cause 30-day readmission	193522	28237 (14.6)	11911/28237 (42.2)	11815/28237 (41.8)	11956/28237 (42.3)	11999/28237 (42.5)
Non-planned 30-day readmission	193522	15988 (8.3)	6209/15988 (38.8)	6269/15988 (39.2)	6321/15988 (39.5)	6308/15988 (39.5)
WA validation (age>=15 years)						

At least one overnight stay	71771	51296 (71.5)	17114/51296 (33.4)	17181/51296 (33.5)	17409/51296 (33.9)	17072/51296 (33.3)
All-cause 30-day readmission	69164	9132 (13.2)	3592/9132 (39.3)	3662/9132 (40.1)	3647/ 9132 (39.9)	3623/9132 (39.7)
Non-planned 30-day readmission	69164	5684 (8.2)	2093/5684 (36.8)	2098/5684 (36.9)	2162/5684 (38.0)	2081/5684 (36.6)

Notes:
Cut-off for classification tables set to maximise sensitivity and specificity
1. Injury severity was not found to be associated with all-cause 30-day readmission, therefore no validation was carried out in this subgroup
2. Intracranial injury = ICD-10-AM codes S06.00 - S06.9
3. Hip fractures = ICD-10 codes S72.0 - S72.2
4. Blunt trauma = ICD-10 codes V00-V99, W00-W19, W20-W24, W30-W31, W50-W52, X50, X79-X82, Y00-Y05 and Y29-Y32
5. Penetrating trauma = ICD-10 codes W53, W54, W55, W57, W58, W59, W25, W26, W27, W28, W29, W45, W32, W34, X72-X74, X78, X93-X95, X99, Y22-Y24 andY28

Table A1: Socio Economic Index for Areas (SEIFA) and country of birth details for the Victorian, NSW and WA study populations

	Patients admitted[1] between July 2012 and June 2014, n (%)											
	Victoria				NSW				WA			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients			161334				233521				84877	
SEIFA state decile[1]												
1	17503	10.8	21.6	0.31 (0.30-0.32)	17879	7.7	20.1	0.29 (0.28-0.30)	1800	2.1	36.2	0.46 (0.43-0.49)
2	**	**	20.3	0.28 (0.27-0.30)	11249	4.8	19.7	0.29 (0.27-0.30)	2359	2.8	25.5	0.33 (0.31-0.36)
3	10595	6.5	22.0	0.32 (0.31-0.33)	12527	5.4	22.4	0.32 (0.31-0.34)	1813	2.1	22.0	0.29 (0.26-0.31)
4	17975	11.1	21.1	0.29 (0.28-0.30)	21142	9.1	21.6	0.31 (0.30-0.32)	5713	6.7	22.7	0.31 (0.29-0.33)
5	10601	6.6	17.6	0.25 (0.24-0.26)	20382	8.7	18.3	0.26 (0.25-0.27)	5656	6.7	21.4	0.29 (0.28-0.31)
6	11830	7.3	18.8	0.27 (0.25-0.28)	30030	12.9	18.7	0.27 (0.26-0.28)	4759	5.6	20.5	0.29 (0.27-0.31)
7	11678	7.3	20.0	0.28 (0.27-0.29)	24255	10.4	18.9	0.27 (0.26-0.28)	10226	12.0	18.2	0.25 (0.24-0.26)
8	25726	16.0	18.9	0.26 (0.26-0.27)	24339	10.4	17.6	0.25 (0.24-0.26)	10719	12.6	20.8	0.29 (0.28-0.30)
9	23873	14.8	19.6	0.27 (0.27-0.28)	31664	13.6	19.2	0.28 (0.28-0.29)	24734	29.1	19.3	0.26 (0.25-0.27)
10	22902	14.2	18.7	0.26 (0.25-0.27)	38996	16.7	16.9	0.25 (0.24-0.25)	16777	19.8	19.2	0.26 (0.25-0.27)
999	*	*	*	*	1058	0.5	33.9	0.45 (0.40-0.49)	321	0.4	34.6	0.42 (0.35-0.50)
Country of birth												
Australia	121134	75.4	17.5	0.24 (0.24-0.24)	178833	76.6	17.6	0.25 (0.25-0.25)	60205	70.9	19.7	0.26 (0.26-0.27)
New Zealand	2397	1.5	13.8	0.18 (0.16-0.20)	4126	1.8	16.5	0.23 (0.21-0.25)	3173	3.7	15.5	0.19 (0.17-0.21)
England	4912	3.0	27.8	0.40 (0.38-0.42)	8043	3.4	24.6	0.36 (0.34-0.37)	6185	7.3	25.1	0.37 (0.35-0.39)
Italy	3474	2.0	42.7	0.68 (0.65-0.71)	2689	1.2	39.3	0.64 (0.60-0.67)	1056	1.2	39.6	0.62 (0.56-0.68)
Greece	2162	1.3	40.0	0.62 (0.58-0.66)	1642	0.7	40.6	0.67 (0.62-0.72)	147	0.2	44.9	0.72 (0.55-0.89)
India	1657	1.1	16.4	0.22 (0.19-0.24)	1607	0.7	15.6	0.22 (0.19-0.25)	699	0.8	26.9	0.41 (0.35-0.48)

All other	25598	15.8	25.0	0.36 (0.35-0.37)	36581	15.7	22.7	0.34 (0.34-0.35)	13412	15.8	20.4	0.29 (0.27-0.30)

Notes:

1. Based on SLAs for Victoria and NSW, and LGAs for WA

Table A2: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (Victoria)

Model	Outcome					
	LOS[1.1]		LOS[1.2]		Hospital costs [2]	
	AUC (95% CI)	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC	Adjusted R^2	Model fit AIC
(viii) Baseline model + presence of at least one comorbidity	0.755 (0.752-0.757)	143989	0.085	575238	0.337	300857
(ix) Baseline model + count of comorbidities	0.756 (0.754-0.759)	143533	0.085	574825	0.345	299579
(x) Baseline model + individual comorbidity (all 31 conditions)	0.760 (0.757-0.763)	142501	0.088	572265	0.359	297336
(xi) Baseline model + selected comorbidities (modelled as a weighted summed score)[3]	0.760 (0.757-0.762)	142570	0.088	572770	0.356	297734
Baseline model deconstructed						
Age	0.636 (0.633-0.639)	161731	0.048	608531	0.057	337677
Age + Sex	0.639 (0.636-0.642)	161619	0.048	607965	0.058	337593
Age + Sex + Body region	0.701 (0.698-0.704)	154187	0.059	597100	0.128	329418
Age + Sex + Body region + Injury type	0.733 (0.730-0.735)	149014	0.074	584880	0.254	313180
Age + Sex + Body region + Injury type + Injury severity	0.744 (0.741-0.746)	146299	0.080	579421	0.309	305191
Age + Sex + Body region + Injury type + SEIFA						
Age + Sex + Body region + Injury type + SEIFA + Geographic region						
Age + Sex + Body region + Injury type + SEIFA + Geographic region + Country of birth						
Age + Sex + Body region + Injury type + Injury severity + SEIFA	0.745 (0.743-0.748)	145954	0.080	579397	0.311	304940
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Country of birth			0.080	579331		

Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region	0.748 (0.745-0.750)	145494		0.311	304824
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region + Country of birth	0.748 (0.745-0.750)	145468		0.312	304799

Notes:

1.1 Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)

1.2 Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges with 1-30 days stay (negative binomial model)

2. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth; outcome= hospital costs (Ln transformed linear model)

3. Actual ORs used as weights, excludes weights resulting from an OR<1.2

Table A2 continued…

Model	Outcome			
	All-cause 30-day readmission[1]		Non-planned 30-day readmission[2]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
(viii) Baseline model + presence of at least one comorbidity	0.621 (0.616-0.625)	98920	0.633 (0.628-0.639)	75142
(ix) Baseline model + count of comorbidities	0.623 (0.618-0.627)	98776	0.635 (0.630-0.640)	75039
(x) Baseline model + individual comorbidity (all 31 conditions)	0.627 (0.622-0.631)	98427	0.639 (0.633-0.644)	74924
(xi) Baseline model + selected comorbidities (modelled as a weighted summed score)[3]	0.625 (0.620-0.629)	98488	0.637 (0.631-0.642)	74953
Baseline model deconstructed				
Age	0.587 (0.582-0.591)	99907	0.588 (0.582-0.593)	76206
Age + Sex	0.587 (0.583-0.592)	99909	0.588 (0.583-0.594)	76206
Age + Sex + Body region	0.602 (0.598-0.607)	99558	0.610 (0.605-0.615)	75799
Age + Sex + Body region + Injury type	0.608 (0.603-0.612)	99342	0.617 (0.611-0.622)	75614

Age + Sex + Body region + Injury type + Injury severity			0.618 (0.612-0.623)	75601
Age + Sex + Body region + Injury type + SEIFA	0.608 (0.604-0.613)	99345		
Age + Sex + Body region + Injury type + SEIFA + Geographic region	0.610 (0.606-0.614)	99286		
Age + Sex + Body region + Injury type + SEIFA + Geographic region + Country of birth	0.611 (0.606-0.615)	99275		
Age + Sex + Body region + Injury type + Injury severity + SEIFA			0.620 (0.614-0.625)	75565
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Country of birth				
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region			0.623 (0.618-0.628)	75455
Age + Sex + Body region + Injury type + Injury severity + SEIFA + Geographic region + Country of birth				

Notes:

1. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all cause 30-day readmission (logistic model)
2. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30 day readmission (logistic model)
3. Actual ORs used as weights, excludes weights resulting from an OR<1.2

Table A3: Performance of new vs existing comorbidity indices using classification tables (Victoria)

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
Baseline	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		68031	12828	80859		12711	72482	85193		6571	51251	57822
		31242	27991	59233		3961	47514	51475		4579	74267	78846
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .66			Classified + if predicted Pr(D)	>= .1			Classified + if predicted Pr(D)	>= .083		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	68.53 %		Sensitivity	Pr(+ D)	76.24%		Sensitivity	Pr(+ D)	58.93%	
	Specificity	Pr(-~D)	68.57 %		Specificity	Pr(-~D)	39.60%		Specificity	Pr(-~D)	59.17%	
	Positive predictive value	Pr(D +)	84.14 %		Positive predictive value	Pr(D +)	14.92%		Positive predictive value	Pr(D +)	11.36%	
	Negative predictive value	Pr(~D -)	47.26 %		Negative predictive value	Pr(~D -)	92.31%		Negative predictive value	Pr(~D -)	94.19%	
	False + rate for true ~D	Pr(+~D)	31.43 %		False + rate for true ~D	Pr(+~D)	60.40%		False + rate for true ~D	Pr(+~D)	40.83%	

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
	False - rate for true D	Pr(- D)	31.47 %		False - rate for true D	Pr(- D)	23.76%		False - rate for true D	Pr(- D)	41.07%	
	False + rate for classified +	Pr(~D +)	15.86 %		False + rate for classified +	Pr(~D +)	85.08%		False + rate for classified +	Pr(~D +)	88.64%	
	False - rate for classified -	Pr(D -)	52.74 %		False - rate for classified -	Pr(D -)	7.69%		False - rate for classified -	Pr(D -)	5.81%	
	Correctly classified		68.54 %		Correctly classified			44.07%	Correctly classified		59.15%	
Baseline + CCI	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		68405	12654	81059		9844	49257	59101		6623	50275	56898
		30868	28165	59033		6828	70739	77567		4527	75243	79770
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .658			Classified + if predicted Pr(D)	>= .121			Classified + if predicted Pr(D)	>= .081		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	68.91 %		Sensitivity	Pr(+ D)	59.05%		Sensitivity	Pr(+ D)	59.40%	

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
	Specificity	Pr(-~D)	69.00 %		Specificity	Pr(-~D)	58.95%		Specificity	Pr(-~D)	59.95%	
	Positive predictive value	Pr(D +)	84.39 %		Positive predictive value	Pr(D +)	16.66%		Positive predictive value	Pr(D +)	11.64%	
	Negative predictive value	Pr(~D -)	47.71 %		Negative predictive value	Pr(~D -)	91.20%		Negative predictive value	Pr(~D -)	94.32%	
	False + rate for true ~D	Pr(+~D)	31.00 %		False + rate for true ~D	Pr(+~D)	41.05%		False + rate for true ~D	Pr(+~D)	40.05%	
	False - rate for true D	Pr(- D)	31.09 %		False - rate for true D	Pr(- D)	40.95%		False - rate for true D	Pr(- D)	40.60%	
	False + rate for classified +	Pr(~D +)	15.61 %		False + rate for classified +	Pr(~D +)	83.34%		False + rate for classified +	Pr(~D +)	88.36%	
	False - rate for classified -	Pr(D -)	52.29 %		False - rate for classified -	Pr(D -)	8.80%		False - rate for classified -	Pr(D -)	5.68%	
	Correctly classified		68.93 %		Correctly classified		58.96%		Correctly classified		59.90%	
Baseline + updated CCI by Quan et al. (2011)	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		68557	12723	81280		9831	49183	59014		6699	51272	57971

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission		
		30716	28096	58812		6841	70813	77654		4451	74246	78697
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .656			Classified + if predicted Pr(D)	>= .122			Classified + if predicted Pr(D)	>= .081		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	69.06 %		Sensitivity	Pr(+ D)	58.97%		Sensitivity	Pr(+ D)	60.08%	
	Specificity	Pr(-~D)	68.83 %		Specificity	Pr(-~D)	59.01%		Specificity	Pr(-~D)	59.15%	
	Positive predictive value	Pr(D +)	84.35 %		Positive predictive value	Pr(D +)	16.66%		Positive predictive value	Pr(D +)	11.56%	
	Negative predictive value	Pr(~D -)	47.77 %		Negative predictive value	Pr(~D -)	91.19%		Negative predictive value	Pr(~D -)	94.34%	
	False + rate for true ~D	Pr(+~D)	31.17 %		False + rate for true ~D	Pr(+~D)	40.99%		False + rate for true ~D	Pr(+~D)	40.85%	
	False - rate for true D	Pr(- D)	30.94 %		False - rate for true D	Pr(- D)	41.03%		False - rate for true D	Pr(- D)	39.92%	
	False + rate for classified +	Pr(~D +)	15.65 %		False + rate for	Pr(~D +)	83.34%		False + rate for classified +	Pr(~D +)	88.44%	

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
					classified +							
	False - rate for classified -	Pr(D -)	52.23 %		False - rate for classified -	Pr(D -)	8.81%		False - rate for classified -	Pr(D -)	5.66%	
	Correctly classified		68.99 %		Correctly classified		59.01%		Correctly classified		59.23%	
Baseline + ECM	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	D	~D	Total
		69211	12370	81581		9882	49021	58903		6713	50131	56844
		30008	28449	58457		6790	70975	77765		4437	75387	79824
	Total	99219	40819	140038	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .651			Classified + if predicted Pr(D)	>= .12			Classified + if predicted Pr(D)	>= .08		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	69.76 %		Sensitivity	Pr(+ D)	59.27%		Sensitivity	Pr(+ D)	60.21%	
	Specificity	Pr(-~D)	69.70 %		Specificity	Pr(-~D)	59.15%		Specificity	Pr(-~D)	60.06%	

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
	Positive predictive value	Pr(D +)	84.84 %		Positive predictive value	Pr(D +)	16.78%		Positive predictive value	Pr(D +)	11.81%	
	Negative predictive value	Pr(~D -)	48.67 %		Negative predictive value	Pr(~D -)	91.27%		Negative predictive value	Pr(~D -)	94.44%	
	False + rate for true ~D	Pr(+~D)	30.30 %		False + rate for true ~D	Pr(+~D)	40.85%		False + rate for true ~D	Pr(+~D)	39.94%	
	False - rate for true D	Pr(- D)	30.24 %		False - rate for true D	Pr(- D)	40.73%		False - rate for true D	Pr(- D)	39.79%	
	False + rate for classified +	Pr(~D +)	15.16 %		False + rate for classified +	Pr(~D +)	83.22%		False + rate for classified +	Pr(~D +)	88.19%	
	False - rate for classified -	Pr(D -)	51.33 %		False - rate for classified -	Pr(D -)	8.73%		False - rate for classified -	Pr(D -)	5.56%	
	Correctly classified		69.74 %		Correctly classified		59.16%		Correctly classified		60.07%	
Baseline + binary injury comorbidity index	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		69180	12377	81557		9839	48937	58776		6710	50539	57249
		30093	28442	58535		6833	71059	77892		4440	74979	79419

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .652			Classified + if predicted Pr(D)	>= .12			Classified + if predicted Pr(D)	>= .08		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	69.69 %		Sensitivity	Pr(+ D)	59.02%		Sensitivity	Pr(+ D)	60.18%	
	Specificity	Pr(-~D)	69.68 %		Specificity	Pr(-~D)	59.22%		Specificity	Pr(-~D)	59.74%	
	Positive predictive value	Pr(D +)	84.82 %		Positive predictive value	Pr(D +)	16.74%		Positive predictive value	Pr(D +)	11.72%	
	Negative predictive value	Pr(~D -)	48.59 %		Negative predictive value	Pr(~D -)	91.23%		Negative predictive value	Pr(~D -)	94.41%	
	False + rate for true ~D	Pr(+~D)	30.32 %		False + rate for true ~D	Pr(+~D)	40.78%		False + rate for true ~D	Pr(+~D)	40.26%	
	False - rate for true D	Pr(- D)	30.31 %		False - rate for true D	Pr(- D)	40.98%		False - rate for true D	Pr(- D)	39.82%	
									False + rate for classified +	Pr(~D +)	88.28%	

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
	False + rate for classified +	Pr(~D +)	15.18 %		False + rate for classified +	Pr(~D +)	83.26%		False - rate for classified -	Pr(D -)	5.59%	
	False - rate for classified -	Pr(D -)	51.41 %		False - rate for classified -	Pr(D -)	8.77%					
									Correctly classified		59.77%	
	Correctly classified		69.68 %		Correctly classified		59.19%					
Baseline + weighted injury comorbidity index	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		69138	12396	81534		9854	49149	59003		6704	50686	57390
		30135	28423	58558		6818	70847	77665		4446	74832	79278
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .654			Classified + if predicted Pr(D)	>= .12						
	True D defined as newsameday!= 0				True D defined as event != 0				Classified + if predicted Pr(D)	>= .08		

Model	At least one overnight stay			All-cause 30-day readmission			Non-planned 30-day readmission		
							True D defined as event != 0		
	Sensitivity	Pr(+ D)	69.64 %	Sensitivity	Pr(+ D)	59.11%			
	Specificity	Pr(-~D)	69.63 %	Specificity	Pr(-~D)	59.04%	Sensitivity	Pr(+ D)	60.13%
	Positive predictive value	Pr(D +)	84.80 %	Positive predictive value	Pr(D +)	16.70%	Specificity	Pr(-~D)	59.62%
	Negative predictive value	Pr(~D -)	48.54 %	Negative predictive value	Pr(~D -)	91.22%	Positive predictive value	Pr(D +)	11.68%
							Negative predictive value	Pr(~D -)	94.39%
	False + rate for true ~D	Pr(+~D)	30.37 %	False + rate for true ~D	Pr(+~D)	40.96%			
	False - rate for true D	Pr(- D)	30.36 %	False - rate for true D	Pr(- D)	40.89%	False + rate for true ~D	Pr(+~D)	40.38%
	False + rate for classified +	Pr(~D +)	15.20 %	False + rate for classified +	Pr(~D +)	83.30%	False - rate for true D	Pr(- D)	39.87%
	False - rate for classified -	Pr(D -)	51.46 %	False - rate for classified -	Pr(D -)	8.78%	False + rate for classified +	Pr(~D +)	88.32%

Model	At least one overnight stay				All-cause 30-day readmission				Non-planned 30-day readmission			
									False - rate for classified -	Pr(D -)	5.61%	
	Correctly classified		69.64 %		Correctly classified		59.05%					
									Correctly classified		59.66%	
Baseline + parsimonious injury comorbidity index	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total	Classified	TRUE D	~D	Total
		69214	12426	81640		9869	49399	59268		6701	50826	57527
		30059	28393	58452		6803	70597	77400		4449	74692	79141
	Total	99273	40819	140092	Total	16672	119996	136668	Total	11150	125518	136668
	Classified + if predicted Pr(D)	>= .651			Classified + if predicted Pr(D)	>= .121			Classified + if predicted Pr(D)	>= .08		
	True D defined as newsameday!= 0				True D defined as event != 0				True D defined as event != 0			
	Sensitivity	Pr(+ D)	69.72 %		Sensitivity	Pr(+ D)	59.20%		Sensitivity	Pr(+ D)	60.10%	
	Specificity	Pr(-~D)	69.56 %		Specificity	Pr(-~D)	58.83%		Specificity	Pr(-~D)	59.51%	

Model	At least one overnight stay			All-cause 30-day readmission			Non-planned 30-day readmission		
	Positive predictive value	Pr(D +)	84.78 %	Positive predictive value	Pr(D +)	16.65%	Positive predictive value	Pr(D +)	11.65%
	Negative predictive value	Pr(~D -)	48.57 %	Negative predictive value	Pr(~D -)	91.21%	Negative predictive value	Pr(~D -)	94.38%
	False + rate for true ~D	Pr(+~D)	30.44 %	False + rate for true ~D	Pr(+~D)	41.17%	False + rate for true ~D	Pr(+~D)	40.49%
	False - rate for true D	Pr(- D)	30.28 %	False - rate for true D	Pr(- D)	40.80%	False - rate for true D	Pr(- D)	39.90%
	False + rate for classified +	Pr(~D +)	15.22 %	False + rate for classified +	Pr(~D +)	83.35%	False + rate for classified +	Pr(~D +)	88.35%
	False - rate for classified -	Pr(D -)	51.43 %	False - rate for classified -	Pr(D -)	8.79%	False - rate for classified -	Pr(D -)	5.62%
	Correctly classified		69.67 %	Correctly classified		58.88%	Correctly classified		59.56%

Table A4: Performance of new comorbidity indices vs existing comorbidity indices in injury sub-groups (Victoria)

Model	Children (<15 years)		Adults (>=65 years)		Males		Females	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
	At least one overnight stay[1]							
Baseline model	0.721 (0.714-0.728)	26030	0.777 (0.772-0.782)	37678	0.730 (0.726-0.733)	84607	0.764 (0.760-0.768)	60340
Baseline model + AICI-os	0.723 (0.717-0.730)	25933	0.803 (0.798-0.807)	36104	0.740 (0.737-0.744)	83177	0.779 (0.775-0.783)	58809
Baseline model + comorbidity using CCI weights	0.722 (0.715-0.729)	26013	0.789 (0.784-0.794)	37021	0.734 (0.730-0.737)	84115	0.769 (0.765-0.773)	59904
Baseline model + comorbidity using ECM	0.724 (0.717-0.731)	25910	0.805 (0.801-0.810)	35906	0.741 (0.738-0.745)	83013	0.780 (0.777-0.784)	58627
Baseline model + AICI-b	0.723 (0.717-0.730)	25933	0.801 (0.797-0.806)	36193	0.740 (0.737-0.744)	83196	0.778 (0.775-0.782)	58870
	All-cause 30-day readmission[2]							
Baseline model	0.654 (0.638-0.670)	9302	0.549 (0.542-0.556)	42952	0.638 (0.631-0.644)	50644	0.581 (0.575-0.587)	48474
Baseline model + AICI-acr	0.660 (0.644-0.676)	9276	0.577 (0.570-0.584)	42500	0.649 (0.643-0.656)	50188	0.599 (0.592-0.605)	48118
Baseline model + comorbidity using CCI weights	0.656 (0.640-0.672)	9296	0.572 (0.565-0.579)	42607	0.646 (0.639-0.652)	50334	0.595 (0.589-0.602)	48185
Baseline model + comorbidity using ECM	0.663 (0.647-0.679)	9258	0.580 (0.573-0.587)	42527	0.651 (0.644-0.657)	50200	0.601 (0.595-0.608)	48132
Baseline model + AICI-r	0.656 (0.640-0.672)	9295	0.570 (0.563-0.577)	42643	0.647 (0.640-0.653)	50309	0.595 (0.588-0.601)	48254
	Non-planned 30-day readmission[3]							
Baseline model	0.663 (0.644-0.682)	6554	0.566 (0.558-0.574)	33663	0.651 (0.644-0.658)	38501	0.595 (0.588-0.603)	36852
Baseline model + AICI-npr	0.665 (0.646-0.684)	6552	0.589 (0.581-0.597)	33406	0.664 (0.656-0.671)	38212	0.611 (0.603-0.618)	36653
Baseline model + comorbidity using CCI weights	0.664 (0.645-0.683)	6555	0.587 (0.579-0.595)	33455	0.658 (0.651-0.665)	38342	0.609 (0.601-0.617)	36664

Baseline model + comorbidity using ECM	0.672 (0.652-0.691)	6527	0.595 (0.587-0.603)	33391	0.665 (0.658-0.673)	38212	0.614 (0.606-0.622)	36636
Baseline model + AICI-r	0.665 (0.645-0.684)	6553	0.586 (0.578-0.594)	33430	0.662 (0.655-0.669)	38236	0.609 (0.601-0.616)	36683
				LOS[4]				
	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC
Baseline model	0.045	32273	0.027	213529	0.079	219966	0.068	231716
Baseline model + AICI-los	0.053	32007	0.032	212380	0.090	217428	0.075	230120
Baseline model + comorbidity using CCI weights	0.047	32215	0.030	212970	0.082	219182	0.071	231196
Baseline model + comorbidity using ECM	0.054	31944	0.033	212162	0.091	217203	0.076	229915
Baseline model + AICI-b	0.053	32013	0.032	212407	0.090	217470	0.075	230136
				Cost[5]				
	Adjusted R^2	Model fit AIC	Adjusted R^3	Model fit AIC	Adjusted R^3	Model fit AIC	Adjusted R^4	Model fit AIC
Baseline model	0.263	46417	0.344	108902	0.273	163891	0.349	140235
Baseline model + AICI-cost	0.274	46169	0.402	105731	0.320	159997	0.397	136675
Baseline model + comorbidity using CCI weights	0.266	46366	0.368	107603	0.289	162597	0.367	138982
Baseline model + comorbidity using ECM	0.277	46106	0.411	105183	0.326	159537	0.406	136014
Baseline model + AICI-b	0.274	46174	0.401	105792	0.319	160093	0.397	136723

Notes:

1. Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)
2. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all-cause 30-day readmission (logistic model)
3. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30-day

readmission (logistic model)

4. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges with 1-30 days stay (negative binomial model)
5. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth; outcome= hospital costs (Ln transformed linear model)

Table A4 continued...

Model	Non-severe injury (adults)		Intracranial injury[1] (adults)		Hip-fracture[2]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
			At least one overnight stay[3]			
Baseline model	84607	138924	0.834 (0.822-0.846)	4552	0.711 (0.709-0.714)	180003
Baseline model + AICI-os	0.717 (0.714-0.720)	136175	0.832 (0.820-0.844)	4484	0.733 (0.730-0.735)	175133
Baseline model + comorbidity using CCI weights	0.707 (0.704-0.710)	138073	0.837 (0.826-0.849)	4524	0.723 (0.720-0.725)	177784
Baseline model + comorbidity using ECM	0.718 (0.716-0.721)	135870	0.831 (0.819-0.843)	4473	0.734 (0.731-0.736)	174741
Baseline model + AICI-b	0.717 (0.714-0.720)	136245	0.831 (0.819-0.843)	4487	0.732 (0.729-0.734)	175397
			All-cause 30-day readmission[4]			
Baseline model			0.649 (0.627-0.671)	3699	0.576 (0.558-0.594)	6238
Baseline model + AICI-acr			0.667 (0.644-0.689)	3671	0.610 (0.592-0.629)	6158
Baseline model + comorbidity using CCI weights			0.666 (0.643-0.688)	3666	0.601 (0.582-0.619)	6174
Baseline model + comorbidity using ECM			0.674 (0.651-0.696)	3686	0.619 (0.601-0.638)	6167
Baseline model + AICI-r			0.663 (0.640-0.685)	3680	0.602 (0.584-0.620)	6186
			Non-planned 30-day readmission[5]			
Baseline model	0.628 (0.622-0.634)	62191	0.658 (0.635-0.682)	3121	0.576 (0.555-0.597)	5113
Baseline model + AICI-npr	0.642 (0.636-0.647)	61771	0.673 (0.649-0.697)	3115	0.601 (0.580-0.622)	5084
Baseline model + comorbidity using CCI weights	0.638 (0.632-0.643)	61900	0.672 (0.647-0.696)	3107	0.594 (0.573-0.614)	5082
Baseline model + comorbidity using ECM	0.643 (0.638-0.649)	61766	0.681 (0.657-0.705)	3129	0.615 (0.594-0.636)	5090

Baseline model + AICI-r	0.640 (0.634-0.646)	61822	0.670 (0.645-0.694)	3116	0.598 (0.577-0.619)	5083
			LOS[6]			
	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC
Baseline model	0.066	355699	0.063	18655	0.000	37609
Baseline model + AICI-los	0.077	351537	0.067	18571	0.001	37594
Baseline model + comorbidity using CCI weights	0.070	354177	0.065	18615	0.000	37611
Baseline model + comorbidity using ECM	0.078	351051	0.069	18533	0.000	37597
Baseline model + AICI-b	0.077	351584	0.067	18572	0.001	37589
			Cost[7]			
	Adjusted R^4	Model fit AIC	Adjusted R^5	Model fit AIC	Adjusted R^5	Model fit AIC
Baseline model	0.174	258804	0.428	14054	0.010	13634
Baseline model + AICI-cost	0.241	251241	0.464	13776	0.060	13363
Baseline model + comorbidity using CCI weights	0.199	256022	0.435	13998	0.016	13597
Baseline model + comorbidity using ECM	0.248	250355	0.472	13710	0.051	13421
Baseline model + AICI-b	0.238	251587	0.462	13786	0.043	13462

Notes:

1. Intracranial injury = ICD-10-AM codes S06.00 - S06.9
2. Hip fractures = ICD-10 codes S72.0 - S72.2
3. Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)
4. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all-cause 30-day readmission (logistic model)
5. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30-day readmission (logistic model)
6. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges with 1-30 days stay (negative binomial model)
7. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth; outcome= hospital costs (Ln transformed linear model)

Table A4 continued....

Model	Blunt trauma[1]		Penetrating trauma[2]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
	At least one overnight stay[3]			
Baseline model	0.779 (0.775-0.782)	88409	0.639 (0.630-0.649)	17039
Baseline model + AICI-os	0.789 (0.785-0.791)	86740	0.651 (0.642-0.661)	16852
Baseline model + comorbidity using CCI weights	0.783 (0.779-0.786)	87763	0.643 (0.634-0.653)	16990
Baseline model + comorbidity using ECM	0.789 (0.786-0.792)	86508	0.651 (0.642-0.660)	16847
Baseline model + AICI-b	0.788 (0.785-0.791)	86801	0.651 (0.642-0.661)	16850
	All-cause 30-day readmission[4]			
Baseline model	0.592 (0.587-0.597)	70900	0.576 (0.558-0.594)	7358
Baseline model + AICI-acr	0.609 (0.603-0.614)	70304	0.600 (0.581-0.618)	7293
Baseline model + comorbidity using CCI weights	0.606 (0.601-0.611)	70442	0.582 (0.564-0.600)	7337
Baseline model + comorbidity using ECM	0.611 (0.605-0.616)	70309	0.605 (0.586-0.623)	7281
Baseline model + AICI-r	0.605 (0.600-0.611)	70463	0.591 (0.573-0.609)	7324
	Non-planned 30-day readmission[5]			
Baseline model	0.602 (0.596-0.608)	54966	0.583 (0.560-0.606)	5188
Baseline model + AICI-npr	0.617 (0.611-0.623)	54609	0.604 (0.581-0.627)	5158
Baseline model + comorbidity using CCI weights	0.613 (0.607-0.619)	54713	0.590 (0.567-0.613)	5172
Baseline model + comorbidity using ECM	0.621 (0.614-0.627)	54560	0.614 (0.591-0.637)	5148
Baseline model + AICI-r	0.615 (0.609-0.621)	54640	0.604 (0.581-0.627)	5156
	LOS[6]			
	McFadden's Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC
Baseline model	0.074	333109	0.038	30897

Baseline model + AICI-los	0.080	331008	0.062	30112
Baseline model + comorbidity using CCI weights	0.077	332208	0.041	30775
Baseline model + comorbidity using ECM	0.081	330737	0.063	30081
Baseline model + AICI-b	0.080	331045	0.062	30118
		Cost[7]		
	Adjusted R[6]	Model fit AIC	Adjusted R[6]	Model fit AIC
Baseline model	0.355	216229	0.175	25933
Baseline model + AICI-cost	0.394	211588	0.209	25481
Baseline model + comorbidity using CCI weights	0.371	214309	0.184	25810
Baseline model + comorbidity using ECM	0.400	210863	0.211	25457
Baseline model + AICI-b	0.394	211660	0.208	25486

Notes:

1. Blunt trauma = ICD-10 codes V00-V99, W00-W19, W20-W24, W30-W31, W50-W52, X50, X79-X82, Y00-Y05, Y29-Y32 and Y85
2. Penetrating trauma = ICD-10 codes W53, W54, W55, W57,W58,W59,W25,W26,W27,W28,W29,W45,W32,X72-X74,X78,X93-X95,X99,Y22-Y24 andY28
3. Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)
4. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all-cause 30-day readmission (logistic model)
5. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30-day readmission (logistic model)
6. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges with 1-30 days stay (negative binomial model)
7. Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth; outcome= hospital costs (Ln transformed linear model)

Table A5: Presence of comorbidity with mean LOS and proportion of patients with readmission outcomes in the NSW and WA study populations (>=15 years)

Comorbidity	NSW			
	Index LOS (n=201791)	Readmissions (n=193522)	All-cause 30-day readmission	Non-planned 30-day readmission

	n (%)	Index LOS (mean, 95% CI)	n (%)	% with condition that had the outcome	% with condition that had the outcome
HIV/AIDS	49 (0.0)	4.8 (2.6-6.9)	43 (0.0)	11.6	*
Alcohol dependence	10970 (5.4)	6.2 (5.9-6.5)	10209 (5.3)	16.4	11.1
Drug dependence	3108 (1.5)	7.2 (6.5-7.9)	2777 (1.4)	19.1	14.3
Any malignancy	846 (0.4)	21.0 (19.4-22.6)	595 (0.3)	34.8	25.9
Blood loss anemia	152 (0.1)	28.9 (23.6-34.3)	137 (0.1)	23.4	16.8
Cardiac arrhythmias	5588 (2.8)	20.7 (20.0-21.5)	5023 (2.6)	20.6	14.5
Cerebrovascular disease	1078 (0.5)	24.3 (22.4-26.2)	964 (0.5)	20.0	15.2
Chronic pulmonary disease	1676 (0.8)	20.1 (18.9-21.3)	1466 (0.8)	25.3	19.2
Coagulopathy	1225 (0.6)	22.6 (20.7-24.4)	1062 (0.5)	23.7	18.1
Congestive heart failure	1407 (0.7)	28.1 (26.6-29.6)	1100 (0.6)	25.5	19.8
Deficiency anemias	683 (0.3)	25.3 (22.8-27.7)	637 (0.3)	25.3	18.2
Dementia	5694 (2.8)	14.4 (13.9-15.0)	5180 (2.7)	16.8	14.4
Depression	5713 (2.8)	10.3 (9.6-10.9)	5530 (2.9)	18.7	12.0
Diabetes with chronic complications	4466 (2.2)	19.8 (18.9-20.7)	4089 (2.1)	25.7	18.1
Diabetes without complications	10717 (5.3)	12.2 (11.7-12.6)	10191 (5.3)	18.6	12.8
Hemiplegia/paraplegia	962 (0.5)	27.9 (25.1-30.7)	867 (0.4)	20.1	13.8
Hypertension complicated	44 (0.0)	23.0 (16.0-30.1)	36 (0.0)	25.0	13.9
Hypertension uncomplicated	7057 (3.5)	21.5 (20.8-22.2)	6447 (3.3)	20.7	13.6
Hypothyroidism	312 (0.2)	23.3 (19.9-26.6)	295 (0.2)	22.4	14.9
Metastatic solid tumor	477 (0.2)	20.1 (18.2-22.1)	301 (0.2)	37.9	29.2
Mild liver disease	1351 (0.7)	12.8 (11.1-14.6)	1194 (0.6)	23.1	16.3
Moderate or severe liver disease	159 (0.1)	26.5 (19.6-33.4)	126 (0.1)	32.5	25.4
Myocardial infarction	455 (0.2)	23.8 (21.4-26.2)	365 (0.2)	20.8	15.6
Obesity	501 (0.3)	26.5 (22.4-30.6)	475 (0.2)	22.7	15.2

Peptic ulcer disease	105 (0.1)	22.6 (16.3-28.9)	91 (0.0)	17.6	9.9
Peripheral vascular disease	447 (0.2)	27.8 (24.2-31.4)	407 (0.2)	26.0	16.2
Psychoses	937 (0.5)	26.9 (22.6-31.2)	872 (0.5)	22.9	17.7
Pulmonary circulation disorders	349 (0.2)	35.8 (30.9-40.8)	275 (0.1)	25.5	19.3
Renal disease including renal failure	3457 (1.7)	22.3 (21.4-23.2)	2995 (1.5)	29.8	19.4
Rheumatic disease including some other connective tissue disorders	307 (0.2)	24.4 (21.0-27.7)	287 (0.1)	19.2	12.9
Valvular disease	551 (0.3)	25.1 (22.8-27.4)	484 (0.3)	22.7	16.1

Table A5 continued.....

Comorbidity	WA				
	Index LOS (n=71771)		Readmissions (n=69164)	All-cause 30-day readmission	Non-planned 30-day readmission
	n (%)	Index LOS (mean, 95% CI)	n (%)	% with condition that had the outcome	% with condition that had the outcome
HIV/AIDS	24 (0.0)	4.8 (1.8-7.8)	20 (0.0)	35.0	*
Alcohol dependence	6307 (8.8)	4.3 (4.0-4.6)	5873 (3.0)	16.9	13.2
Drug dependence	1347 (1.9)	4.6 (4.0-5.2)	1235 (0.6)	18.6	15.9
Any malignancy	307 (0.4)	17.1 (14.3-19.9)	220 (0.1)	47.3	24.5
Blood loss anemia	105 (0.2)	20.6 (15.9-25.3)	92 (0.0)	17.4	13.0
Cardiac arrhythmias	1516 (2.1)	18.3 (16.8-19.9)	1353 (0.7)	22.0	16.2
Cerebrovascular disease	352 (0.5)	26.0 (20.9-31.0)	320 (0.2)	23.4	18.4
Chronic pulmonary disease	442 (0.6)	17.0 (15.0-19.0)	393 (0.2)	25.2	18.8
Coagulopathy	517 (0.7)	20.4 (17.6-23.1)	445 (0.2)	22.5	15.3
Congestive heart failure	429 (0.6)	22.7 (20.4-25.1)	341 (0.2)	24.9	19.6
Deficiency anemias	216 (0.3)	20.1 (16.1-24.0)	204 (0.1)	19.6	13.7
Dementia	1534 (2.1)	15.2 (13.9-16.5)	1335 (0.7)	17.9	15.9

Depression	1266 (1.8)	7.7 (6.6-8.9)	1222 (0.6)	25.6	16.8
Diabetes with chronic complications	1726 (2.4)	14.9 (13.7-16.1)	1592 (0.8)	27.3	19.1
Diabetes without complications	4349 (6.1)	9.5 (8.9-10.2)	4162 (2.2)	18.0	13.0
Hemiplegia/paraplegia	338 (0.5)	28.1 (22.3-34.0)	306 (0.2)	20.9	14.4
Hypertension complicated	29 (0.0)	21.4 (10.7-32.1)	25 (0.0)	40.0	28.0
Hypertension uncomplicated	2077 (2.9)	18.8 (17.6-19.9)	1884 (1.0)	24.8	17.5
Hypothyroidism	73 (0.1)	25.1 (18.7-31.4)	68 (0.0)	14.7	8.8
Metastatic solid tumor	157 (0.2)	15.9 (13.4-18.4)	101 (0.1)	50.5	25.7
Mild liver disease	550 (0.8)	9.0 (7.5-10.6)	483 (0.2)	19.3	15.3
Moderate or severe liver disease	55 (0.1)	18.5 (10.6-26.4)	40 (0.0)	35.0	22.5
Myocardial infarction	126 (0.2)	25.9 (20.9-30.8)	99 (0.1)	20.2	17.2
Obesity	140 (0.2)	23.2 (17.2-29.3)	133 (0.1)	18.8	14.3
Peptic ulcer disease	55 (0.1)	17.5 (11.2-23.7)	50 (0.0)	22.0	*
Peripheral vascular disease	391 (0.5)	16.0 (13.8-18.3)	364 (0.2)	15.7	9.6
Psychoses	182 (0.3)	15.0 (11.5-18.4)	175 (0.1)	35.4	25.7
Pulmonary circulation disorders	91 (0.1)	34.1 (20.9-47.2)	71 (0.0)	23.9	16.9
Renal disease including renal failure	1095 (1.5)	17.6 (16.0-19.1)	969 (0.5)	36.8	24.6
Rheumatic disease including some other connective tissue disorders	107 (0.2)	22.7 (17.7-27.7)	99 (0.1)	28.3	16.2
Valvular disease	159 (0.2)	21.9 (18.3-25.6)	143 (0.1)	18.9	14.0

Notes:
*Cell count 1-4 suppressed to protect confidentiality

Table A6: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (NSW and WA)

Model	$LOS^{1.1}$		$LOS^{1.2}$	
	AUC (95% CI)	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC

		NSW		
(i) Baseline model	0.736 (0.734-0.739)	208244	0.076	658947
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.748 (0.746-0.751)	204746	0.084	653296
(iii) Baseline model + selected comorbidities (modelled as a weighted summed score)[3]	0.747 (0.745-0.750)	205238	0.084	653595
(iv) Baseline model + comorbidity using CCI weights	0.740 (0.737-0.742)	207318	0.079	657108
(v) Baseline model + comorbidity using Quan weights	0.739 (0.736-0.741)	207568	0.078	657511
(vi) Baseline model + ECM	0.750 (0.748-0.752)	204129	0.086	652310
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.748 (0.746-0.751)	204744	0.084	653340

		WA		
(i) Baseline model	0.718 (0.714-0.722)	76512	0.093	226149
(v) Baseline model + individual comorbidity (selected) (binary representation)	0.731 (0.728-0.735)	75272	0.102	223901
(vi) Baseline model + comorbidity using ICI (integer value of actual weight)	0.729 (0.725-0.733)	75563	0.102	224038
(vii) Baseline model + comorbidity using CCI weights	0.723 (0.719-0.727)	76035	0.096	225330
(viii) Baseline model + comorbidity using Quan weights	0.722 (0.719-0.726)	76115	0.095	225536
(ix) Baseline model + ECM	0.734 (0.730-0.737)	75048	0.103	223586
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.731 (0.727-0.735)	75281	0.102	223932

Note:

1.1 Baseline model includes age, sex, injury severity, injury type, body region, geographic region, SEIFA deciles and country of birth; outcome =overnight stay discharge (logistic model)

1.2 Baseline model includes age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth; outcome = LOS of non-same day discharges

with 1-30 days stay (negative binomial model)

Table A6 continued....

Model	All-cause 30-day readmission[1]		Non-planned 30-day readmission[2]	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
	NSW			
(i) Baseline model	0.594 (0.590-0.597)	158291	0.629 (0.625-0.633)	107407
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.604 (0.600-0.607)	157706	0.641 (0.636-0.645)	106765
(iii) Baseline model + selected comorbidities (modelled as a weighted summed score)	0.603 (0.599-0.606)	157729	0.640 (0.636-0.645)	106795
(iv) Baseline model + comorbidity using CCI weights	0.600 (0.597-0.604)	157906	0.637 (0.633-0.642)	106966
(v) Baseline model + comorbidity using Quan weights	0.598 (0.595-0.602)	158057	0.636 (0.631-0.640)	107052
(vi) Baseline model + ECM	0.605 (0.602-0.608)	157666	0.643 (0.639-0.647)	106704
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.602 (0.598-0.605)	157830	0.639 (0.634-0.643)	106891
	WA			
(i) Baseline model	0.625 (0.619-0.631)	52550	0.656 (0.648-0.663)	37822
(v) Baseline model + individual comorbidity (selected) (binary representation)	0.639 (0.633-0.645)	52091	0.673 (0.665-0.680)	37462
(vi) Baseline model + comorbidity using ICI (integer value of actual weight)	0.638 (0.632-0.644)	52121	0.671 (0.664-0.678)	37505
(vii) Baseline model + comorbidity using CCI weights	0.633 (0.626-0.638)	52307	0.663 (0.656-0.670)	37666
(viii) Baseline model + comorbidity using Quan weights	0.631 (0.625-0.637)	52389	0.661 (0.654-0.668)	37714
(ix) Baseline model + ECM	0.641 (0.635-0.647)	52106	0.676 (0.668-0.683)	37450
(vii) Baseline model + 23 comorbidities common to LOS and cost outcomes (binary representation)/Baseline model + 8 comorbidities common to readmission outcomes (binary representation)	0.635 (0.629-0.641)	52238	0.670 (0.663-0.677)	37515

Note:

1. Baseline model includes age, sex, injury type, body region, geographic region and country of birth; outcome=all cause 30-day readmission (logistic model)
2. Baseline model includes age, sex, injury severity, injury type, body region, geographic region and SEIFA deciles; outcome=non-planned 30 day readmission (logistic model)

Note: See Table 5 for selected comorbidities for each outcome

Table A7: Conditions included in the injury comorbidity indices for burden, readmissions, CCI and ECM

Comorbidity	Outcome								
	Overnight stay (AICI-os)[1]	LOS (AICI-los)[2]	Cost (AICI-cost)[3]	Burden (AICI-b)[4]	All-cause 30-day readmission (AICI-acr)[5]	Non-planned 30-day readmission (AICI-npr)[6]	Readmissions (AICI-r)[7]	CCI	ECM
HIV/AIDS	X	X	X	X	X	X	X	✓	✓
Alcohol dependence	✓	✓	✓	✓	✓	✓	✓	X	✓
Drug dependence	✓	✓	✓	✓	X	✓	X	X	✓
Any malignancy	✓[8]	✓[8]	✓[8]	✓[8]	✓[8]	X	X	✓[8]	✓[9]
Blood loss anaemia	✓	✓	✓	✓	X	X	X	X	✓
Cardiac arrhythmias	✓	✓	✓	✓	X	X	X	X	✓
Cerebrovascular disease	X	✓	X	X	X	X	X	✓	X
Chronic pulmonary disease	✓	✓	✓	✓	✓	✓	✓	✓	✓
Coagulopathy	✓	✓	✓	✓	✓	✓	✓	X	✓
Congestive heart failure	✓	✓	✓	✓	X	✓	X	✓	✓
Deficiency anaemias	✓	✓	✓	✓	X	X	X	X	✓
Dementia	✓	X	✓	X	X	X	X	✓	X
Depression	✓	✓	✓	✓	✓	X	X	X	✓
Diabetes with chronic complications	✓	✓	✓	✓	✓	✓	✓	✓	✓
Diabetes without complications	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fluid and electrolyte disorders	-	-	-	-	-	-	-	-	✓
Hemiplegia/paraplegia	✓	✓	✓	✓	X	X	X	✓	✓
Hypertension complicated	X	X	✓	X	X	X	X	X	✓
Hypertension uncomplicated	✓	✓	✓	✓	X	X	X	X	
Hypothyroidism	✓	✓	✓	✓	X	X	X	X	✓
Metastatic solid tumor	X	✓	X	X	X	✓	X	✓	✓
Mild liver disease	✓	✓	✓	✓	✓	✓	✓	✓	✓
Moderate or severe liver disease	✓	✓	✓	✓	X	X	X	✓	
Myocardial infarction	X	X	✓	X	X	X	X	✓	X

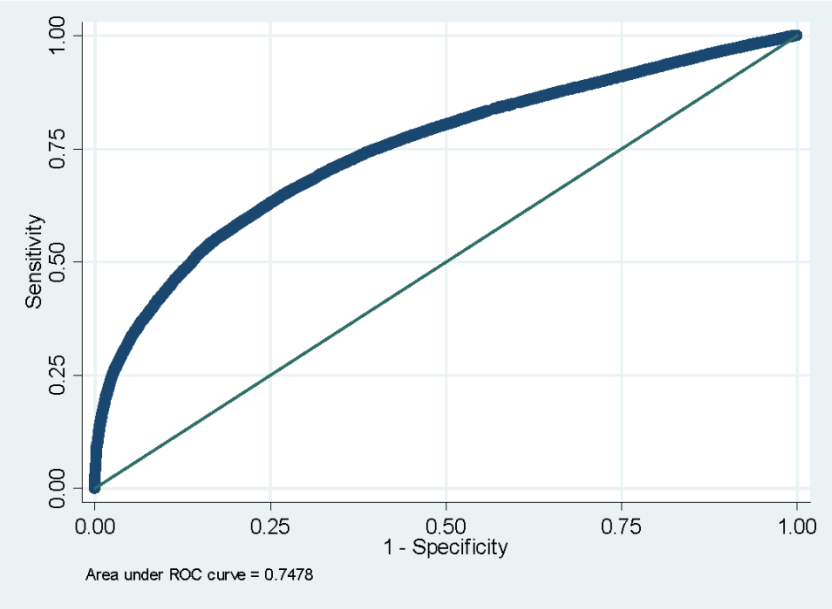
Obesity	✓	✓	✓	✓	X	X	X	X	✓
Other neurological disorders	-	-	-	-	-	-	-	-	✓
Peptic ulcer disease	X	✓	✓	X	X	X	X	✓	✓
Peripheral vascular disease	✓	✓	✓	✓	X	X	X	✓	✓
Psychoses	✓	✓	✓	✓	✓	✓	✓	X	✓
Pulmonary circulation disorders	X	✓	✓	X	X	X	X	X	✓
Renal disease including renal failure	✓	✓	✓	✓	✓	✓	✓	✓	✓
Rheumatic disease including some other connective tissue disorders	✓	✓	✓	✓	X	X	X	✓	✓
Valvular disease	✓	✓	✓	✓	X	X	X	X	✓
Weight loss	-	-	-	-	-	-	-	-	✓

Notes:

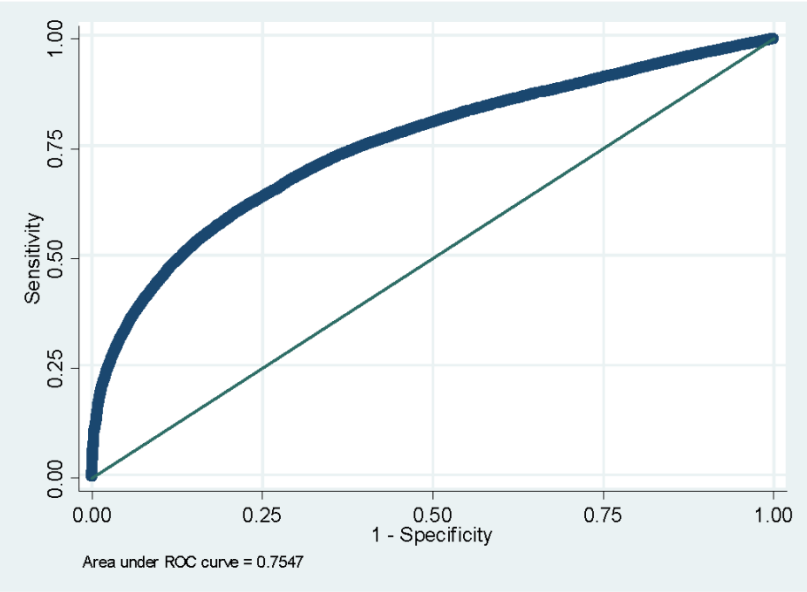
1. AICI-os - Australian Injury Comorbidity Index - overnight stay
2. AICI-los - Australian Injury Comorbidity Index - length of stay for non-same day discharges
3. AICI-cost - Australian Injury Comorbidity Index -direct hospital cost
4. AICI-b - Australian Injury Comorbidity Index - burden (includes cost, overnight stay and LOS for overnight stays)
5. AICI-acr - Australian Injury Comorbidity Index - all-cause 30-day readmission
6. AICI-npr - Australian Injury Comorbidity Index - non-planned 30-day readmission
7. AICI-r -Australian Injury Comorbidity Index - readmissions (includes all-cause and non-planned 30-day readmissions)
8. Includes lymphoma, solid tumors without metastasis and leukaemia
9. Includes lymphoma and solid tumors without metastasis

Appendix A1.1 – ROC curves for overnight stay (age >= 15 years)

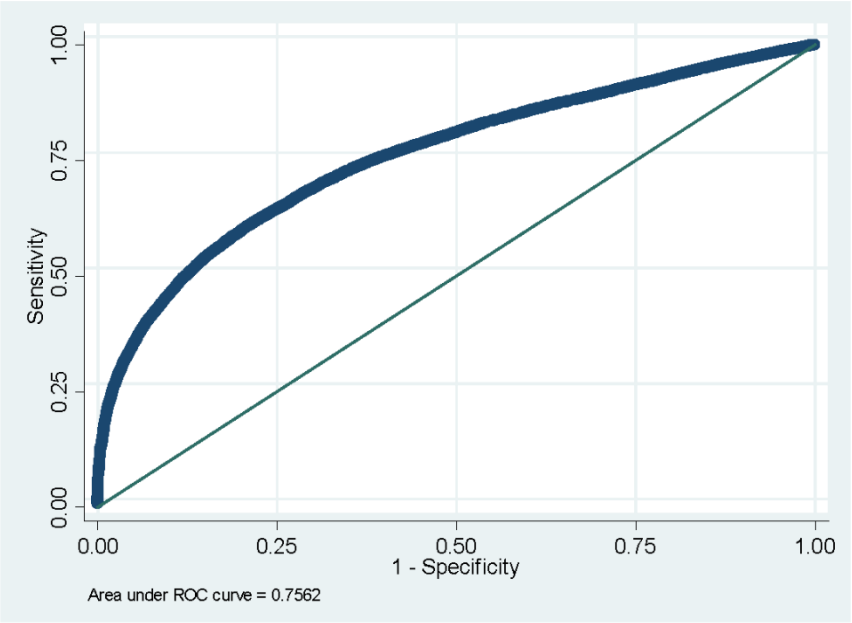
Baseline model (age, sex, body region, injury-type, injury-severity, SEIFA, geographic region and country of birth)



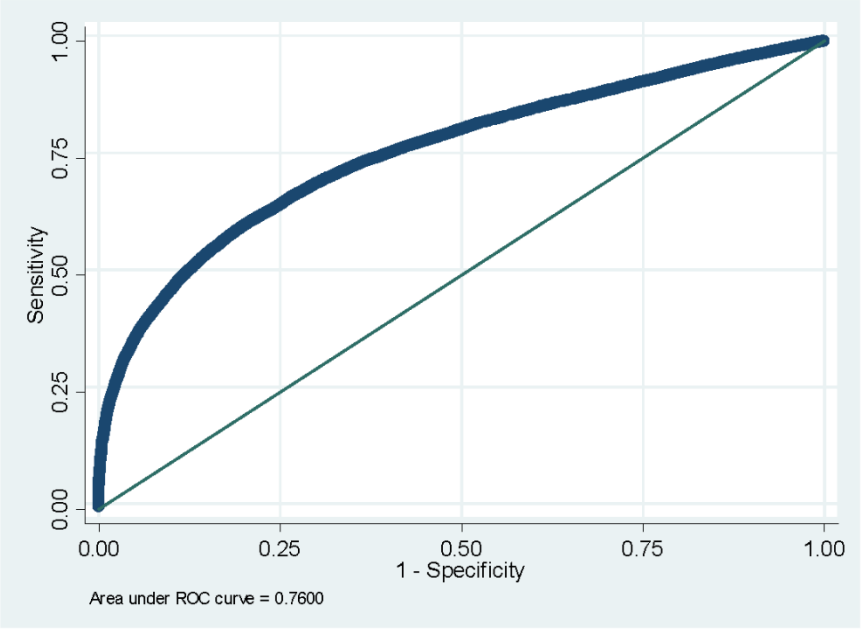
Baseline model + at least one comorbidity



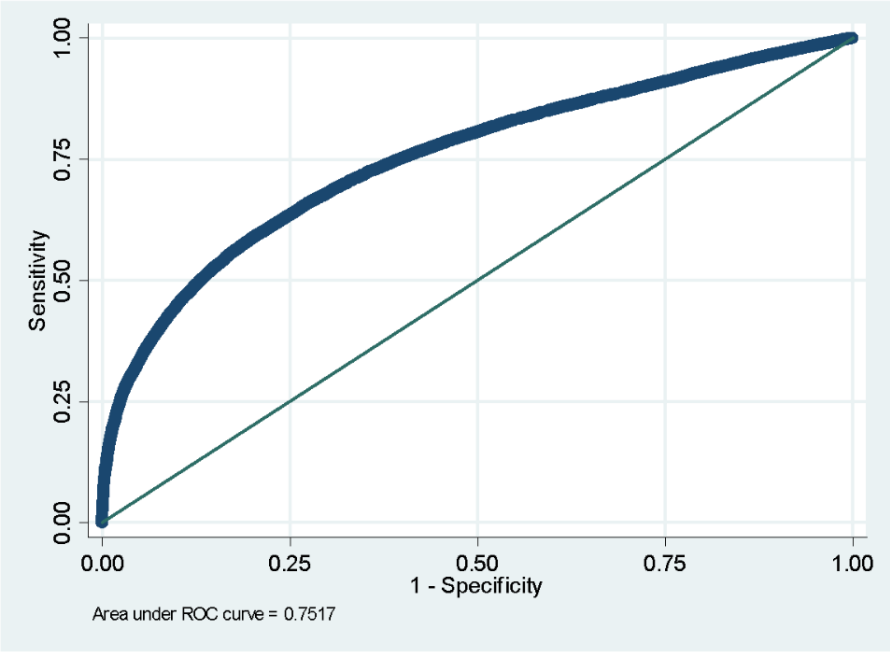
Baseline model + count of comorbidities



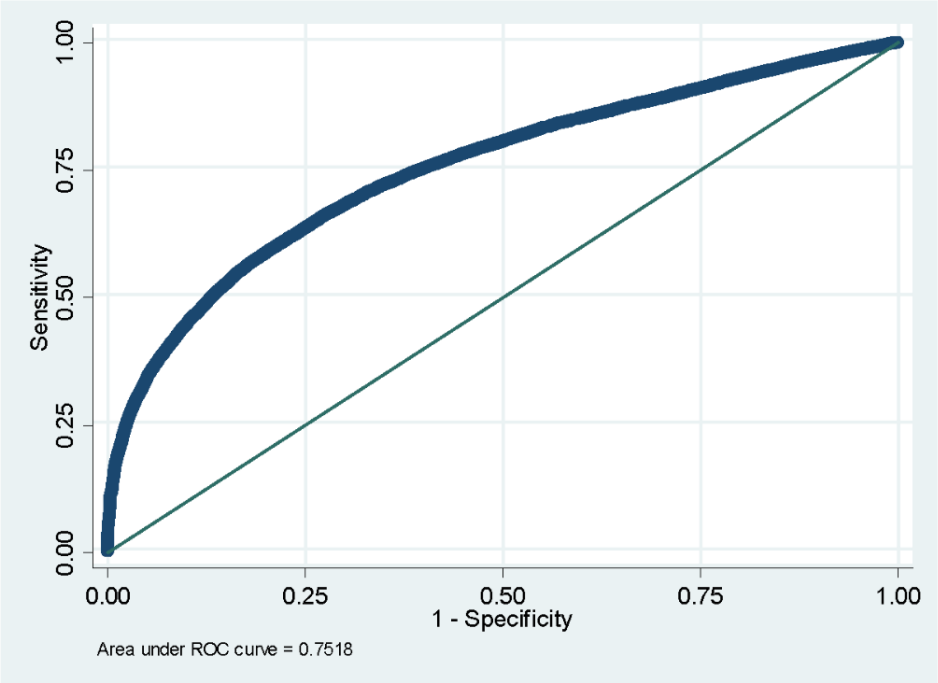
Baseline model + all 31 comorbidities



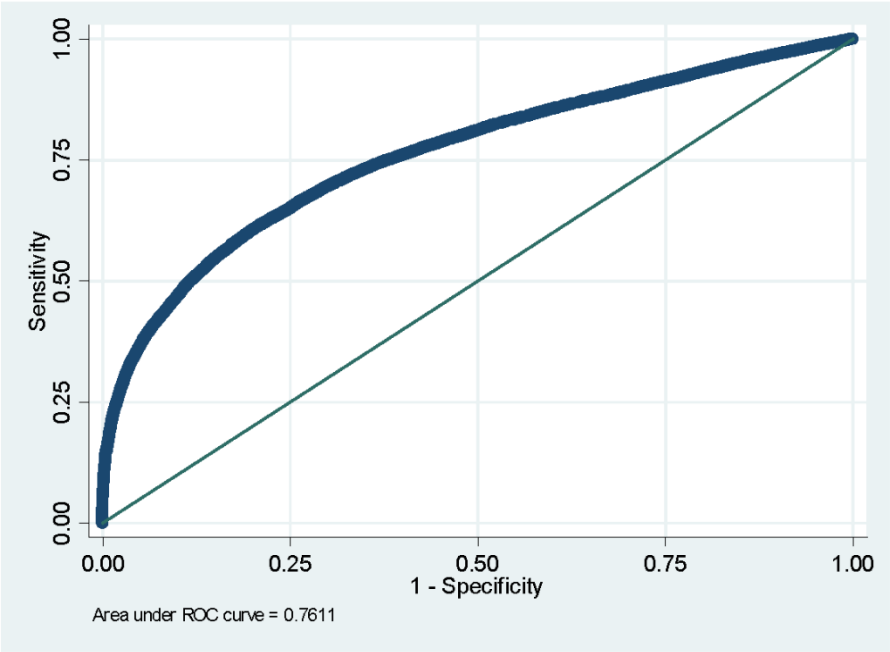
Baseline model + Charlson Comorbidity Index



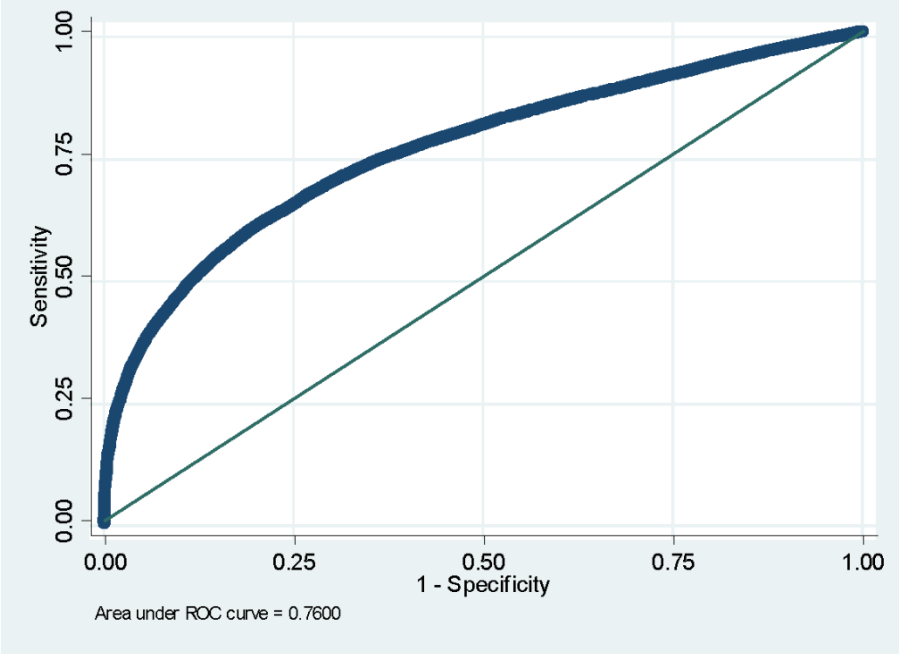
Baseline model + updated CCI per Quan et. al. (2011)



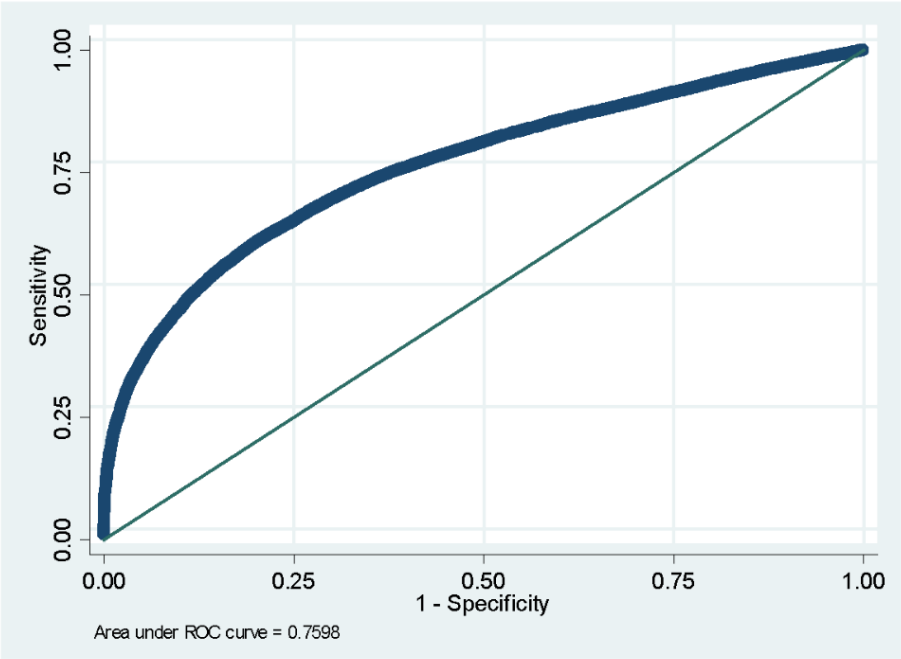
Baseline model + Elixhauser Comorbidity Measure



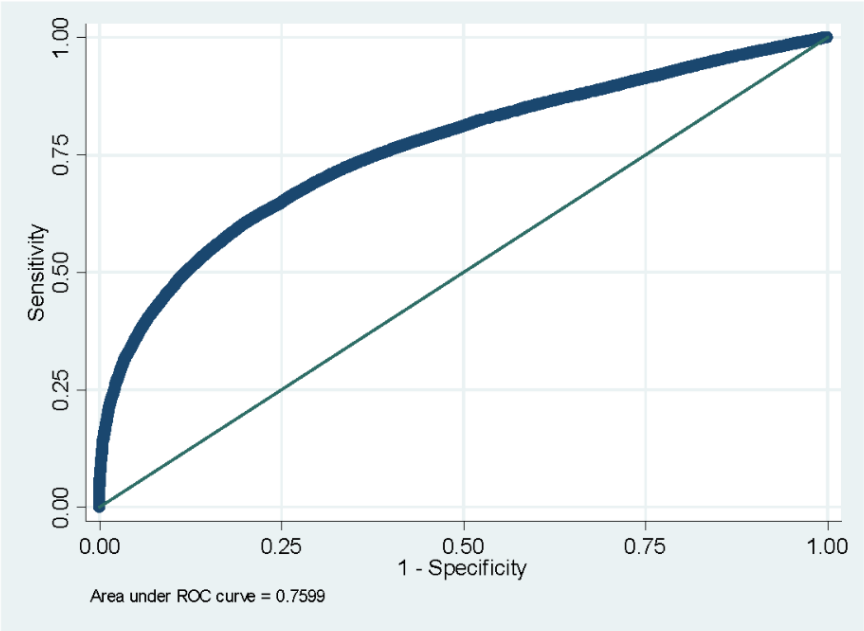
Baseline model + AICI-os (24 conditions, binary representation)



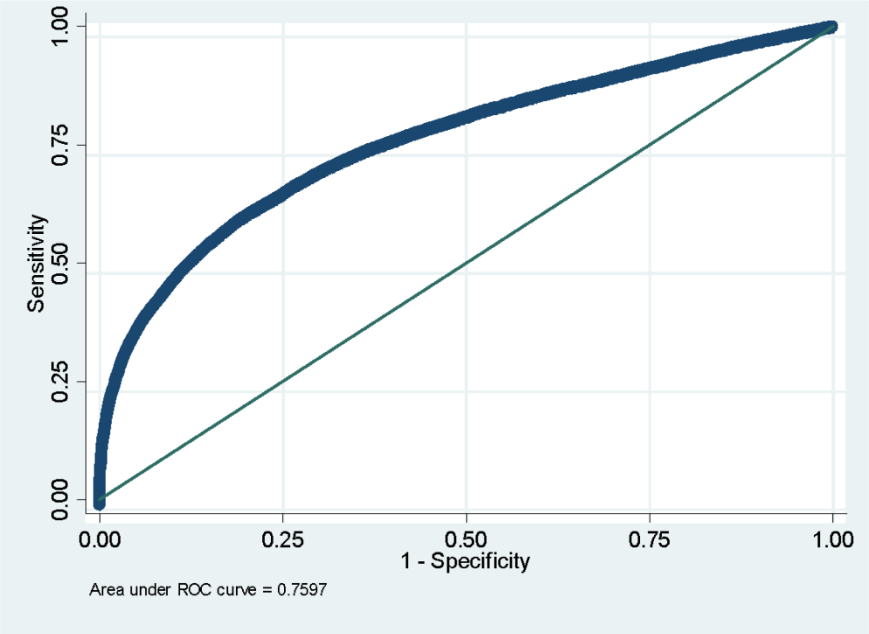
Baseline model + comorbidity index with actual weights (24 conditions)



Baseline model + comorbidity index with rounded weights (24 conditions)

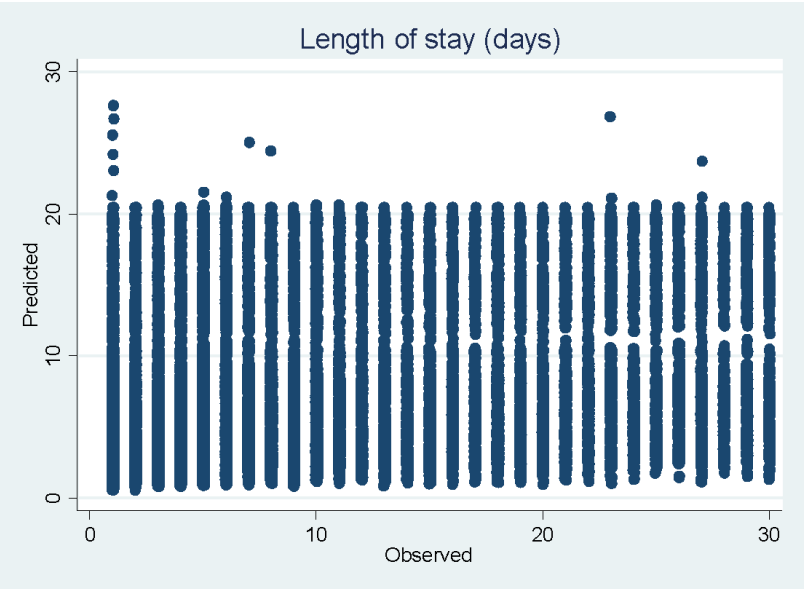


Baseline model + parsimonious index (23 conditions common to all three burden outcomes, binary representation)

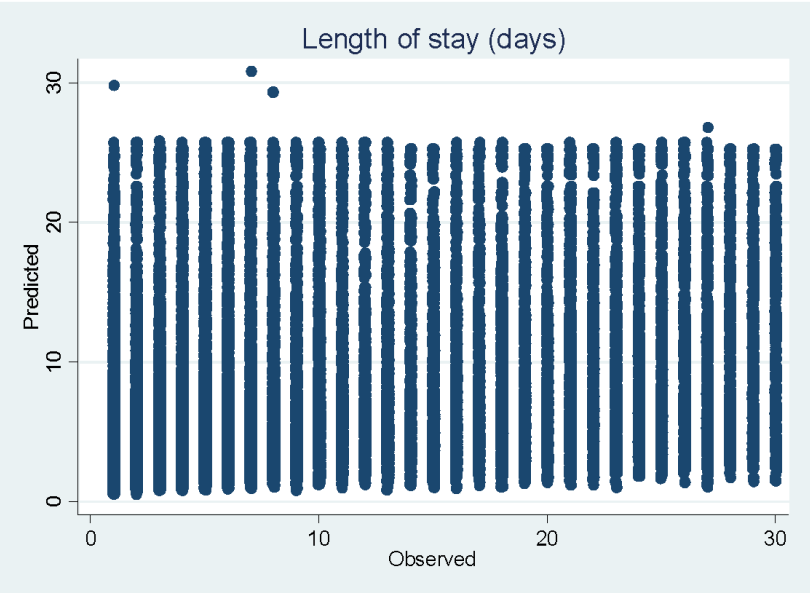


Appendix A1.2 - Plots of predicted length of stay (days) vs observed (at least 1 overnight and LOS<=30)

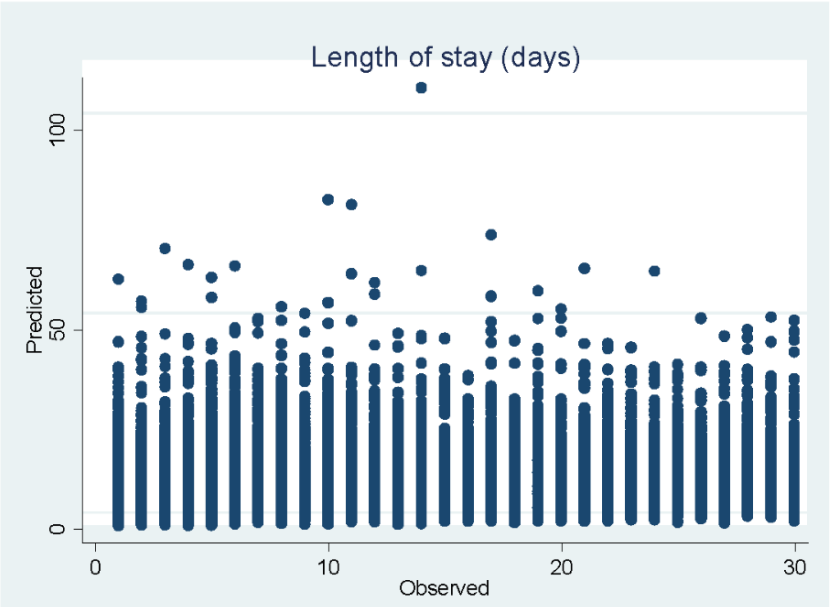
Baseline model (age, sex, injury severity, injury type, body region, SEIFA deciles and country of birth)



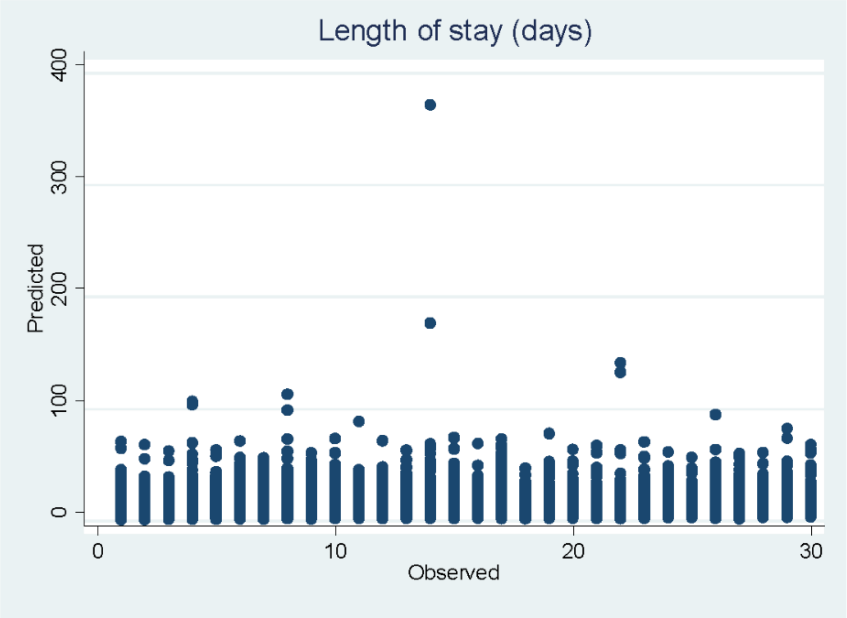
Baseline model + presence of at least one comorbidity



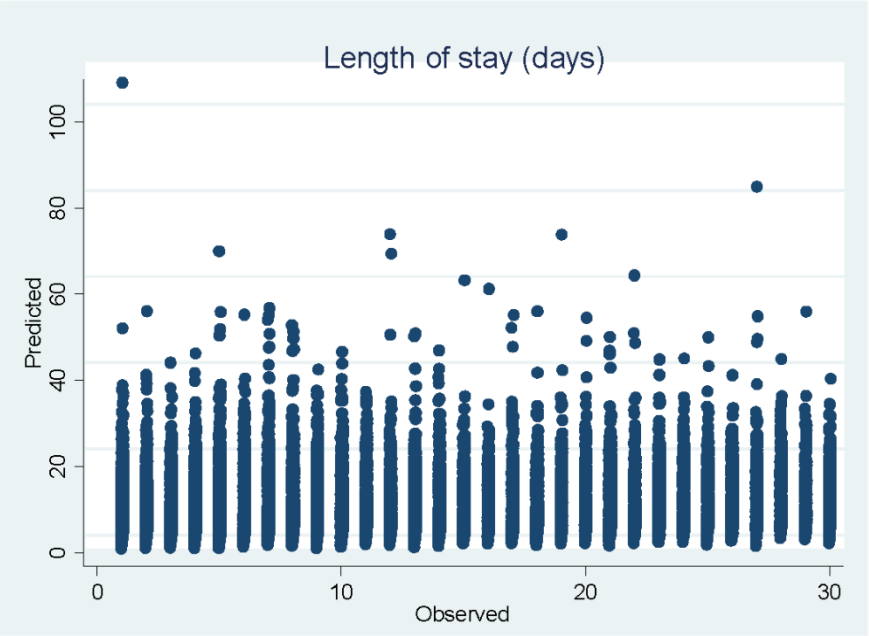
Baseline model + count of all comorbidities



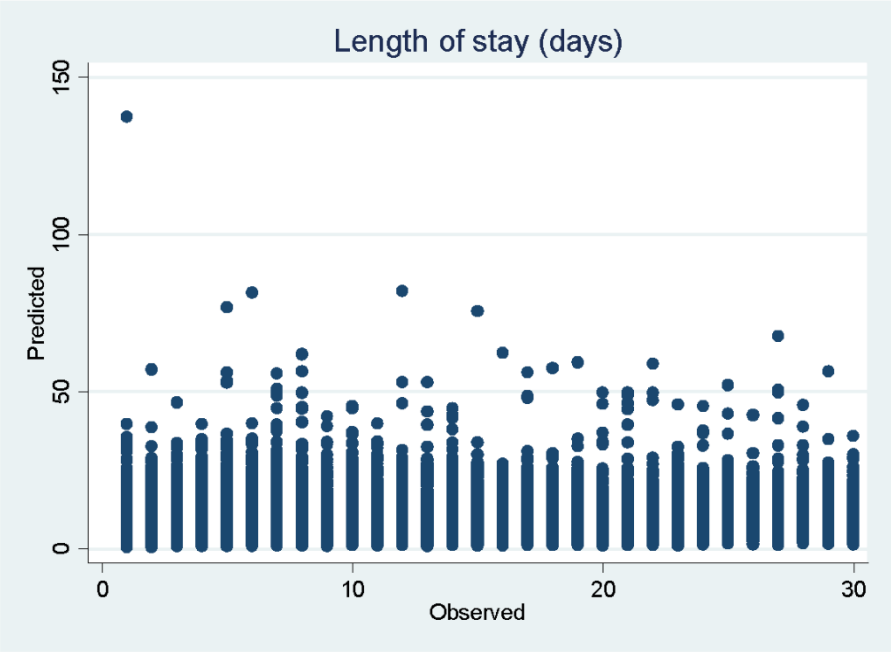
Baseline model + all 31 comorbidities



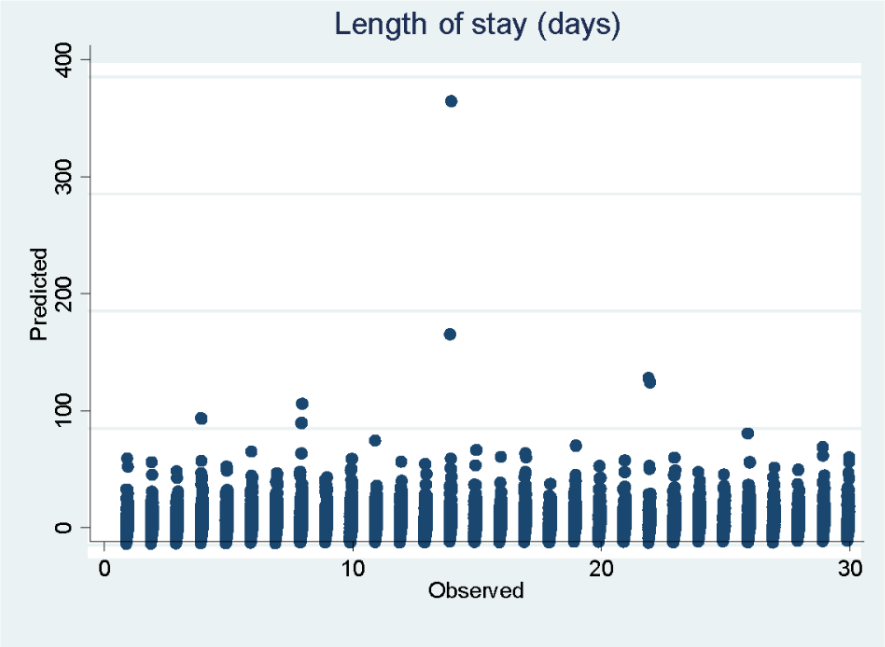
Baseline model + Charlson Comorbidity Index



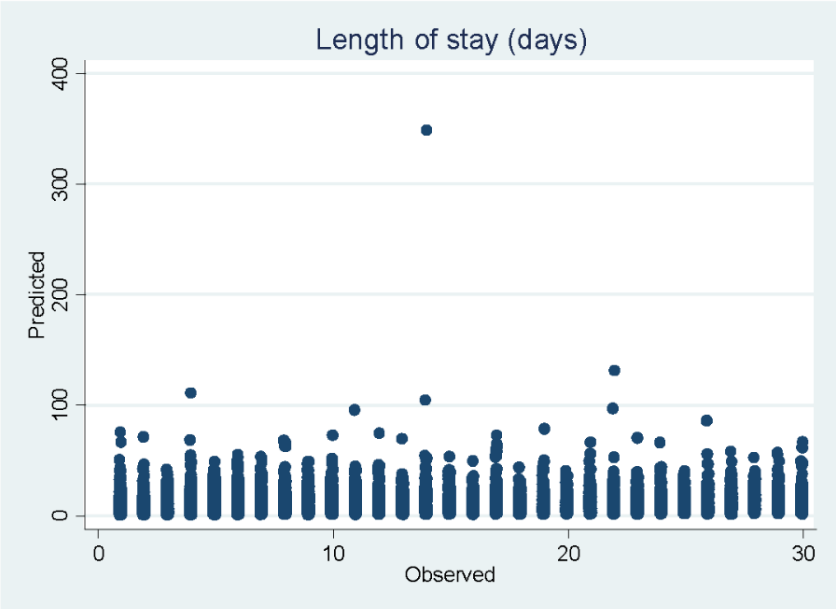
Baseline model + updated CCI per Quan et al. (2011)



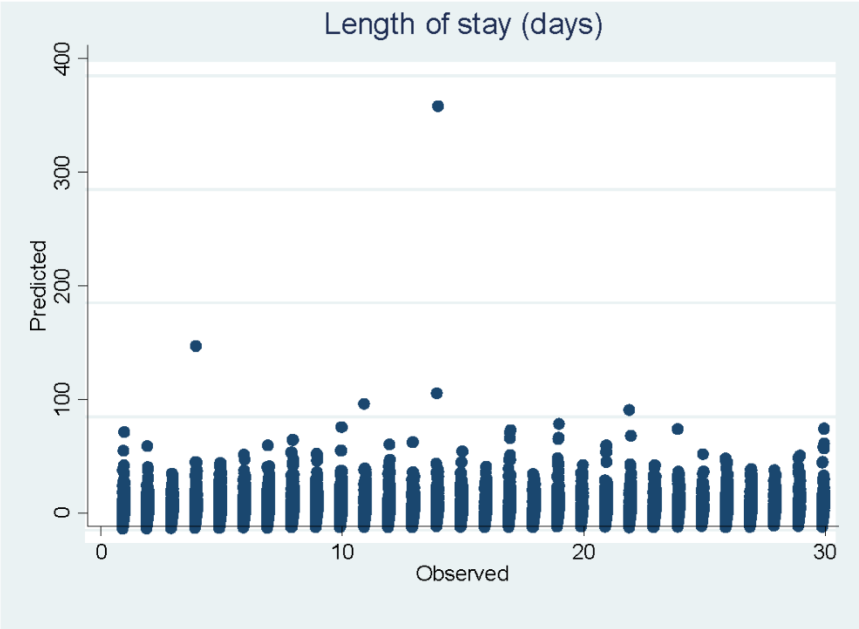
Baseline model + Elixhauser Comorbidity Measure



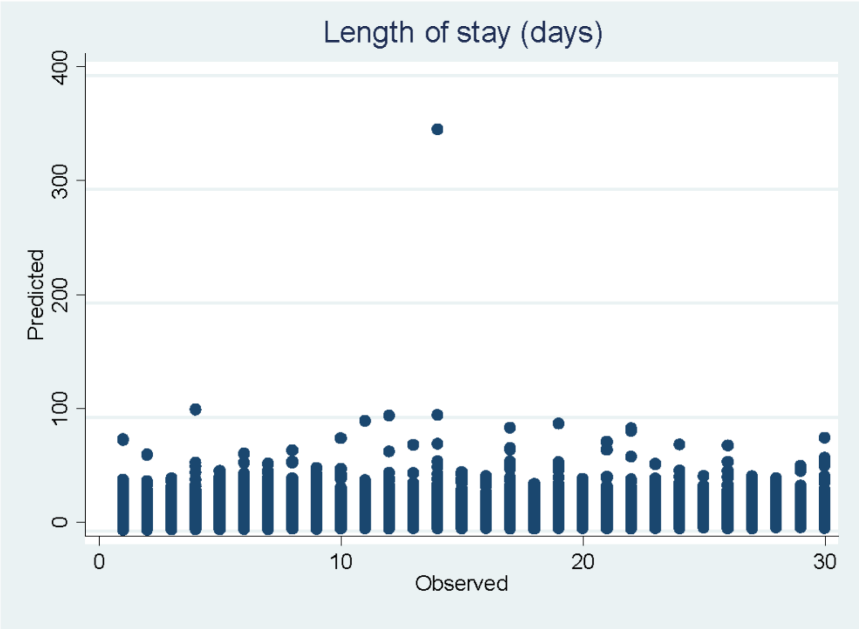
Baseline model + AICI-los (binary representation, 27 conditions)



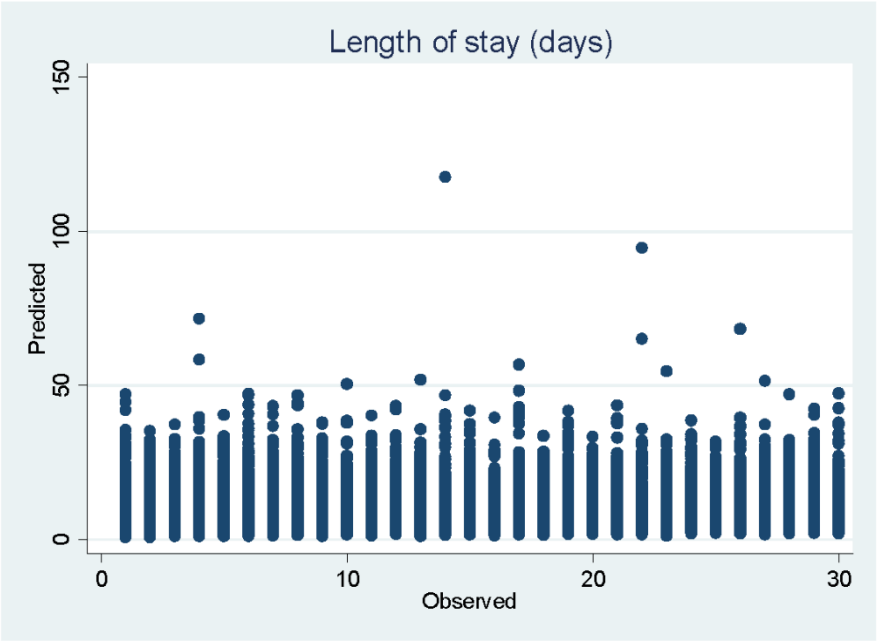
Baseline model + comorbidity index as a weighted summed score using actual weights (23 conditions)



Baseline model + comorbidity index as a weighted summed score using rounded weights (23 conditions)

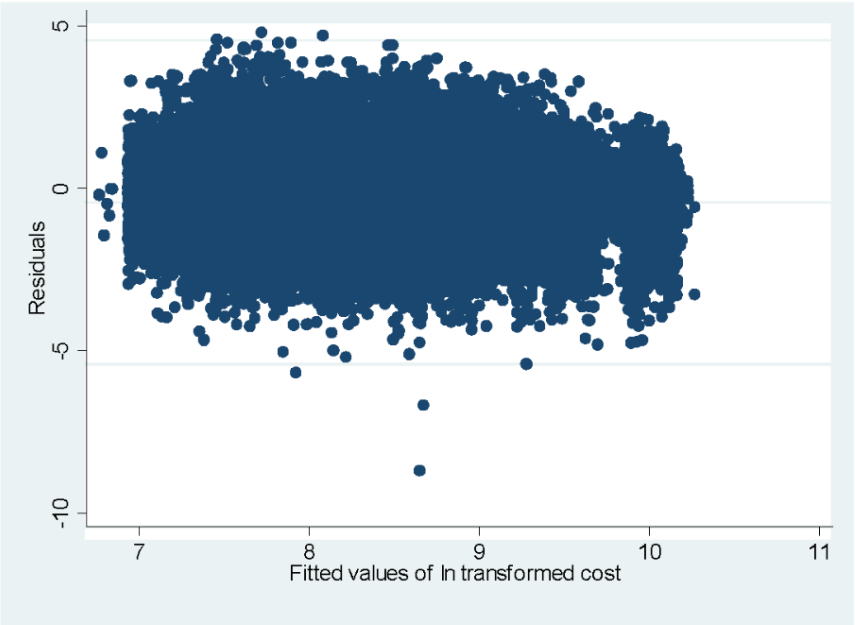


Baseline model + parsimonious index (23 conditions common to burden outcomes, binary representation)

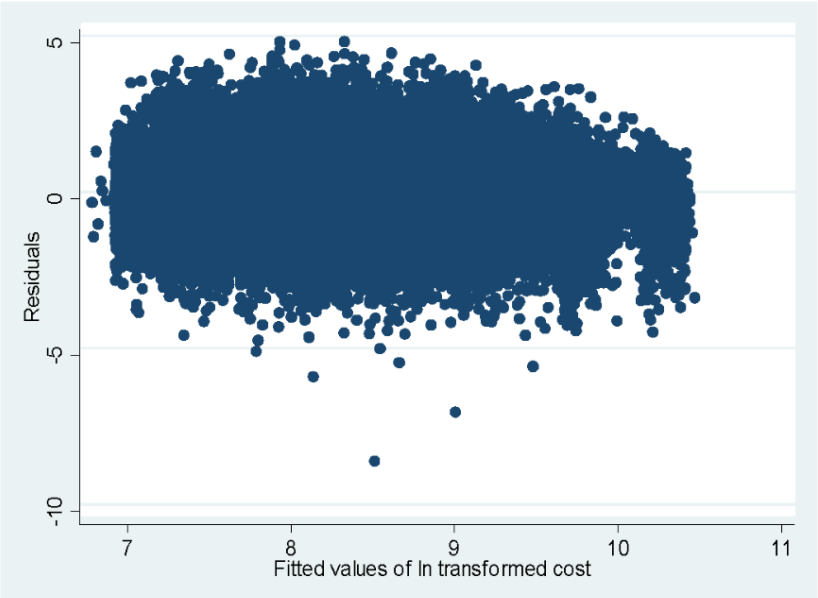


Appendix A1.3 – Residual plots for costs

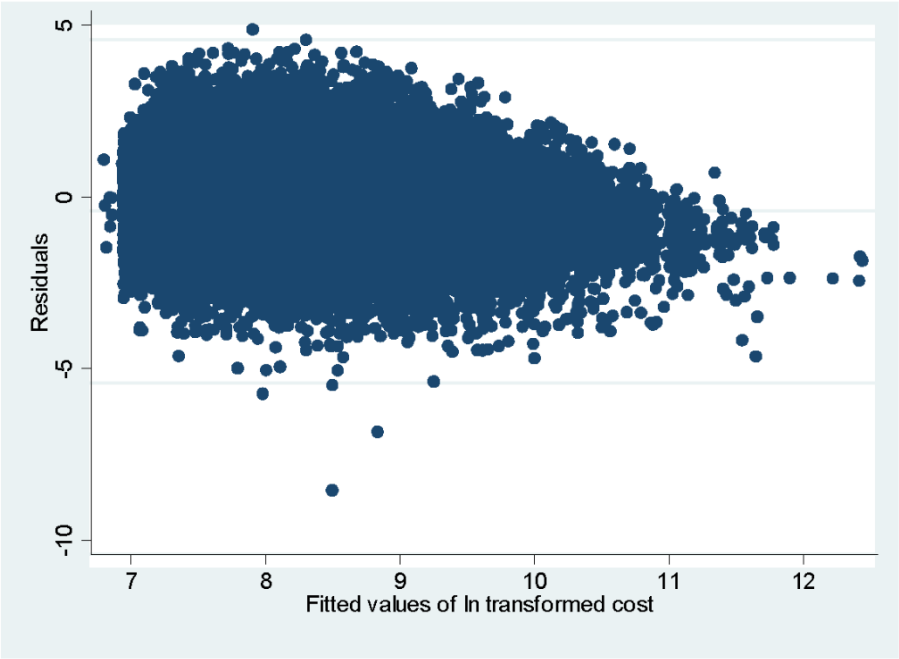
Baseline model (age, sex, injury severity, injury type, body region, SEIFA deciles, geographic region (metropolitan and rural) and country of birth)



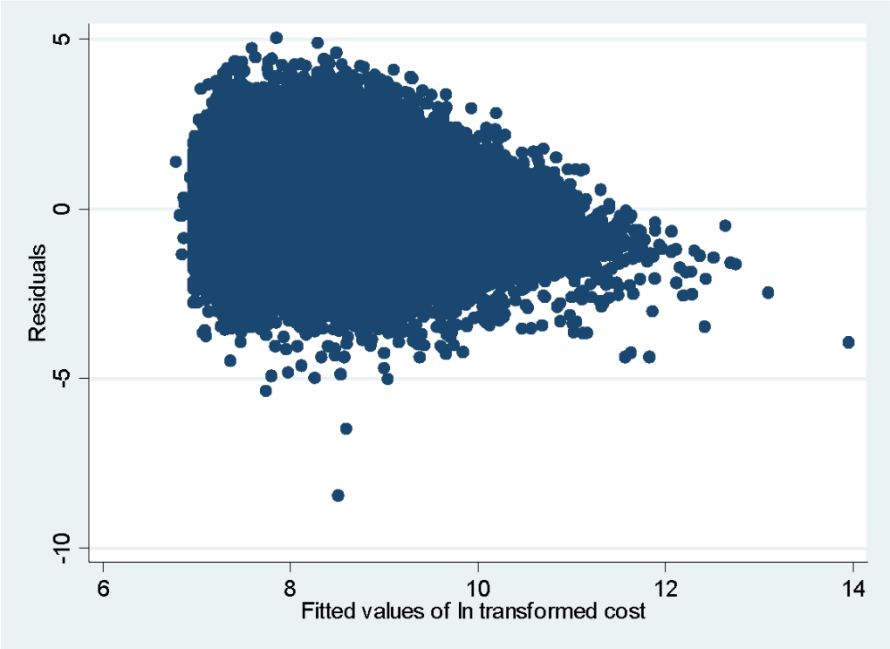
Baseline model + presence of at least one comorbidity



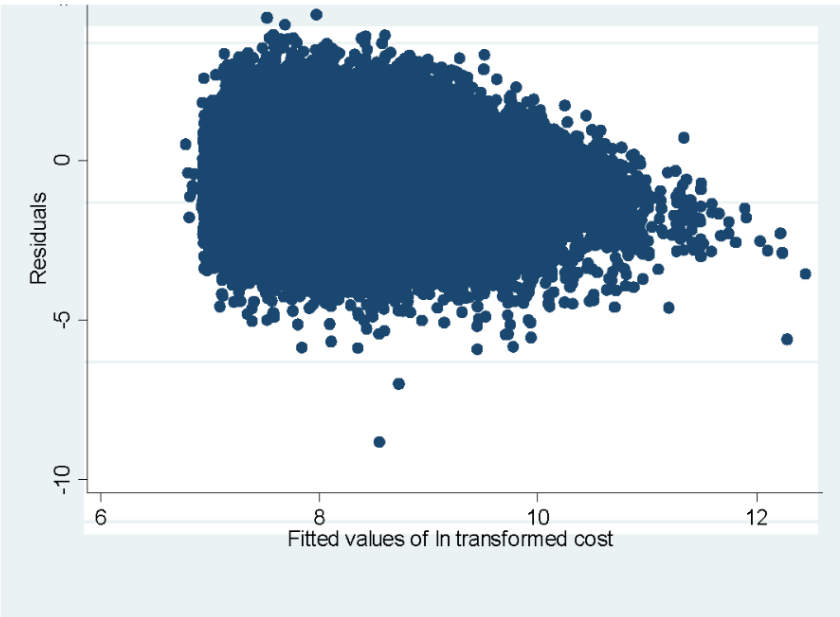
Baseline model + count of all comorbidities



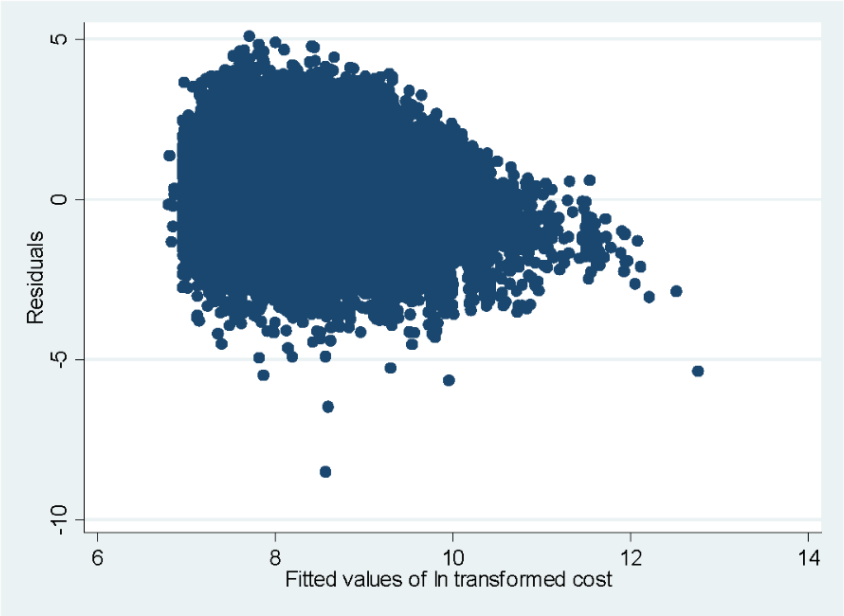
Baseline model + all 31 comorbidities



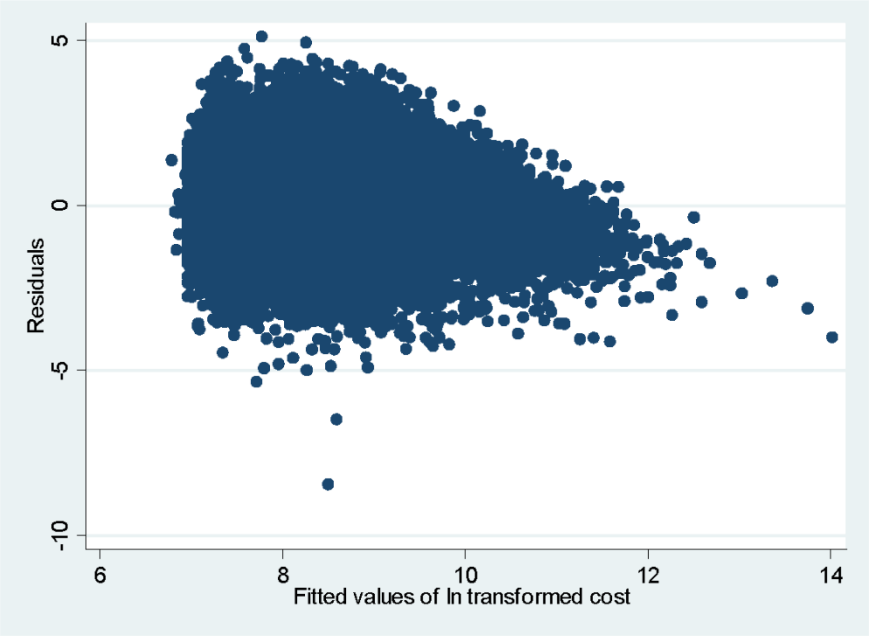
Baseline model + Charlson Comorbidity Index



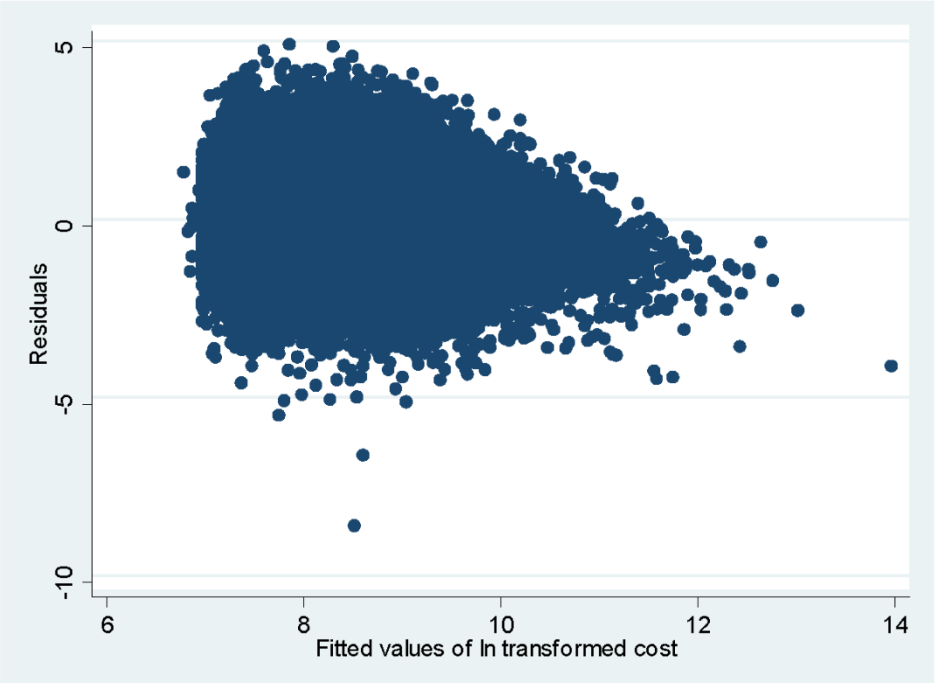
Baseline model + Updated CCI by Quan et. al. (2011)



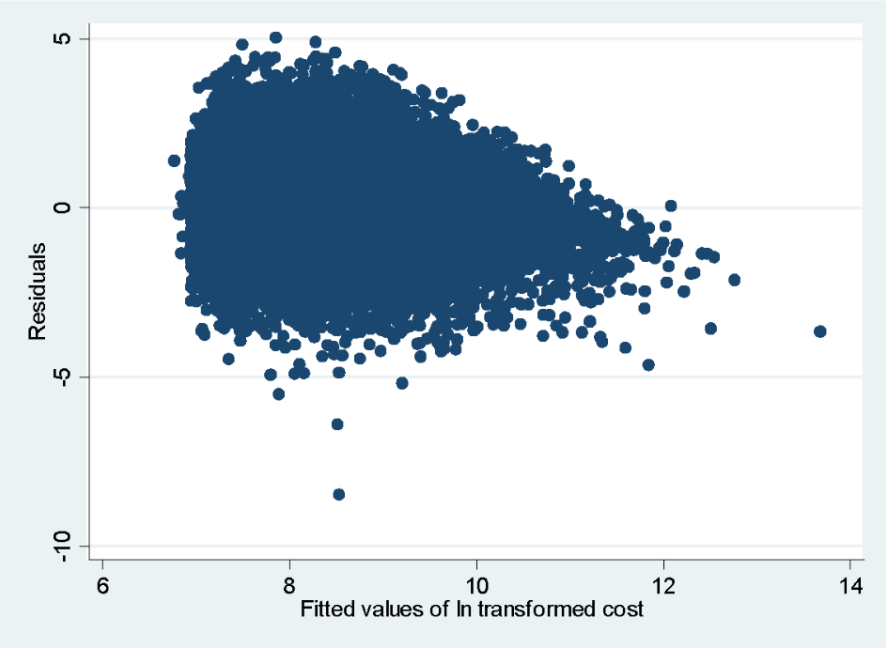
Baseline model + Elixhauser Comorbidity Measure



Baseline model + AICI-cost (binary representation 28 conditions)

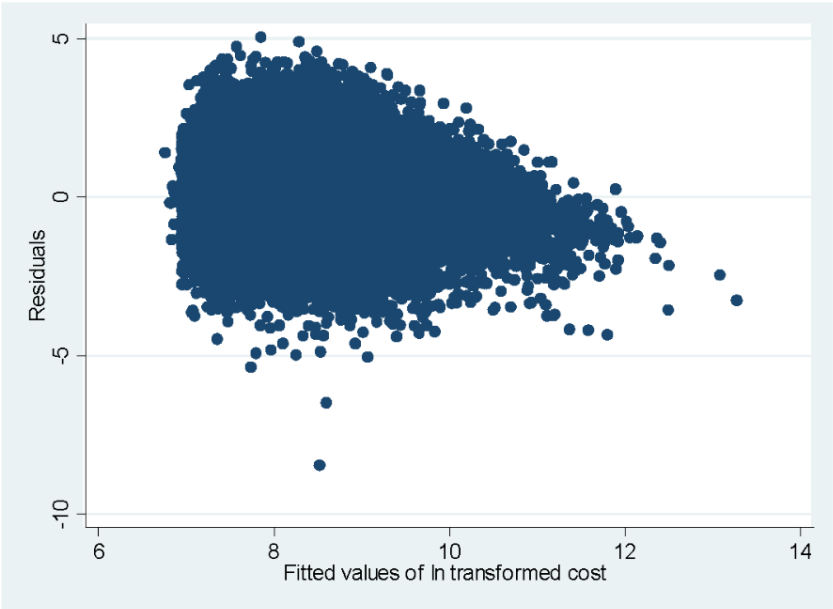


Baseline model + comorbidity index as a weighted summed score using actual weights (26 conditions)



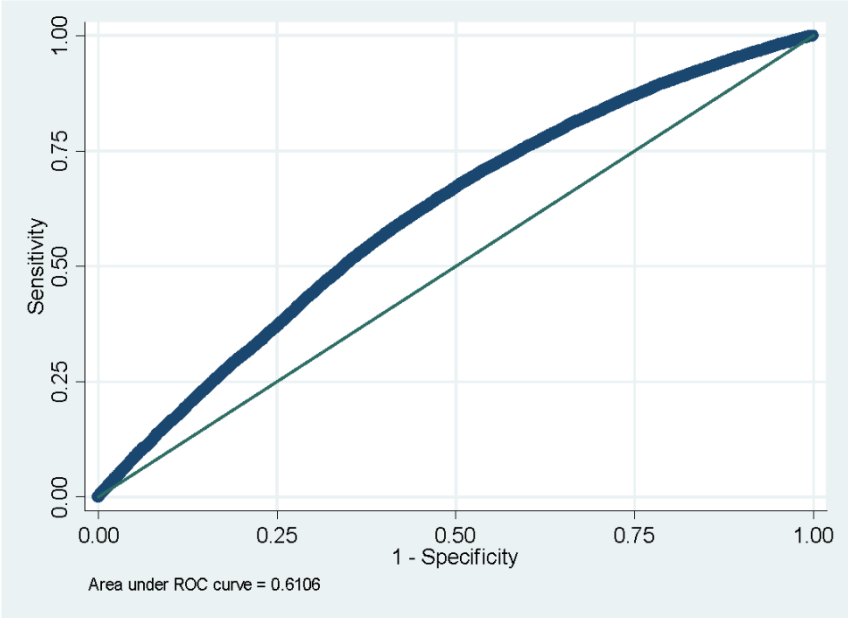
Baseline model + comorbidity index as a weighted summed score using rounded weights (26 conditions)

Baseline model + parsimonious index (23 conditions common to all burden outcomes, binary representation)

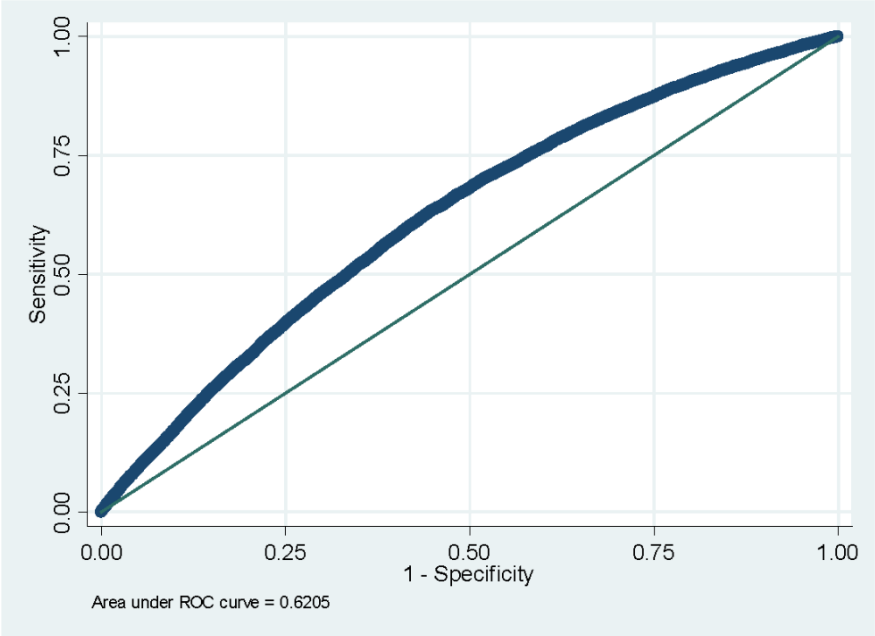


Appendix A1.4 – ROC curves for all-cause 30-day readmissions (age >= 15 years)

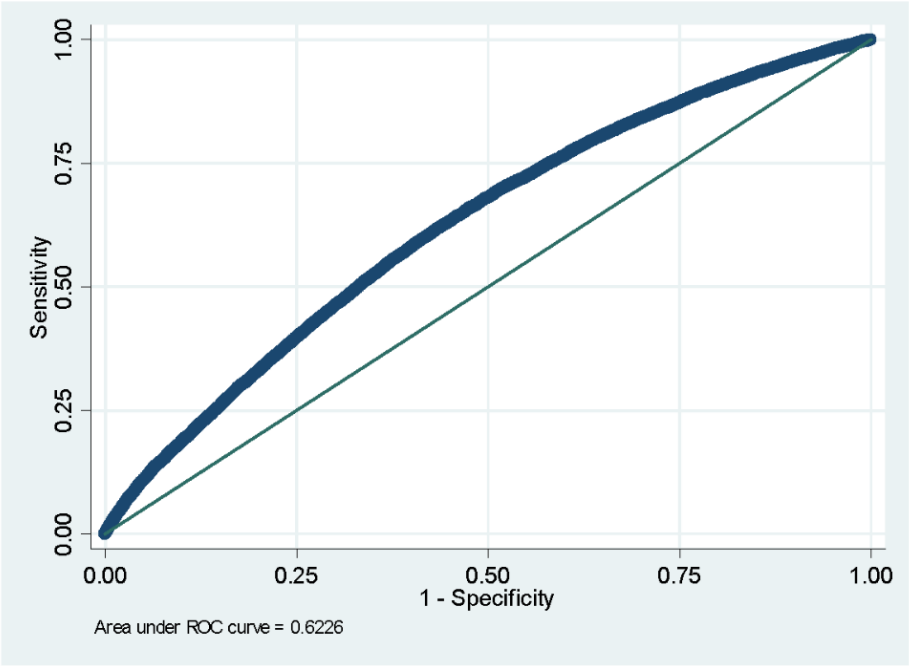
Baseline model (age, sex, body region, injury-type, geographic region and country of birth)



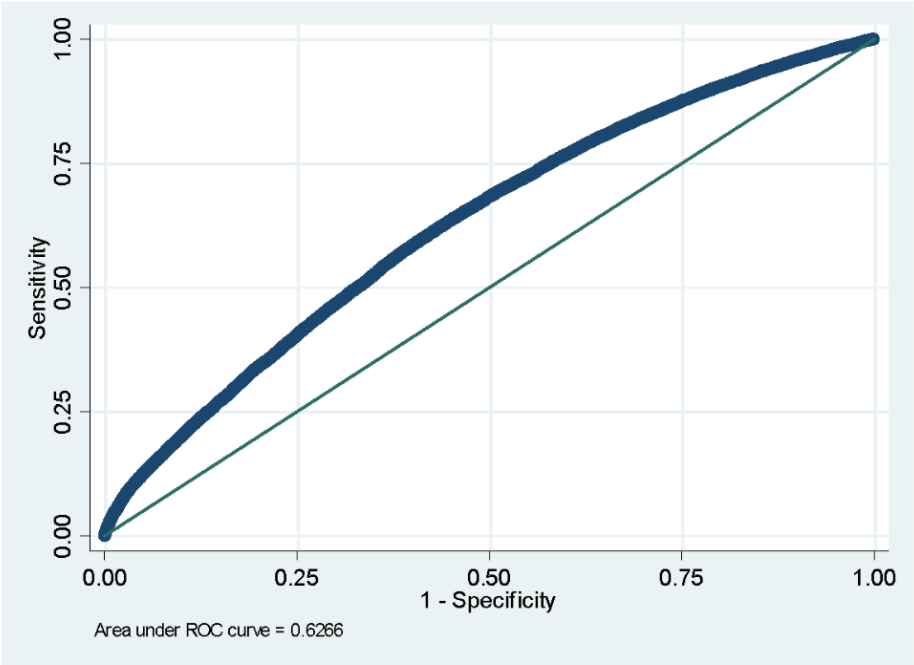
Baseline model + at least one comorbidity



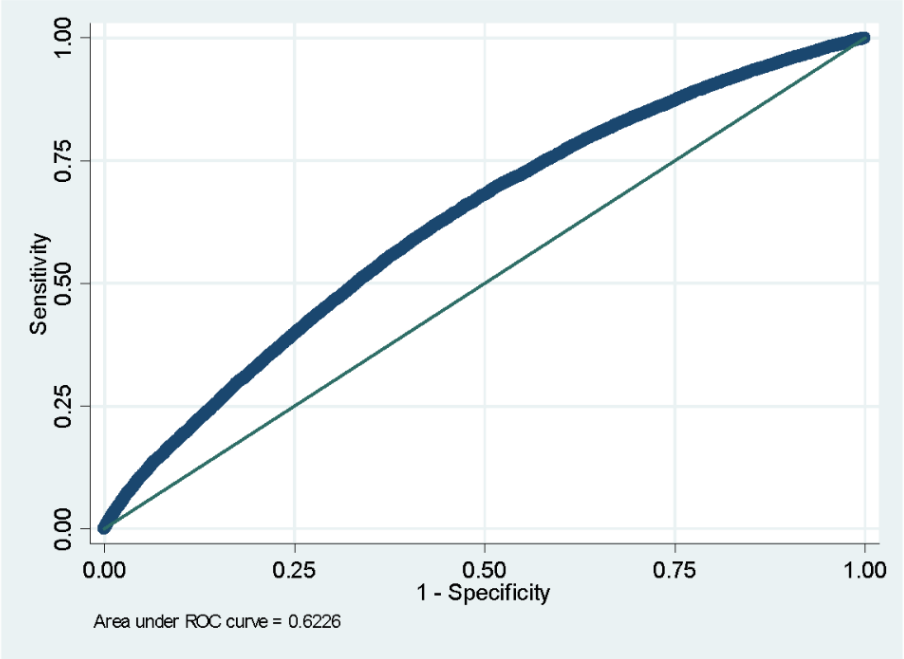
Baseline model + count of comorbidities



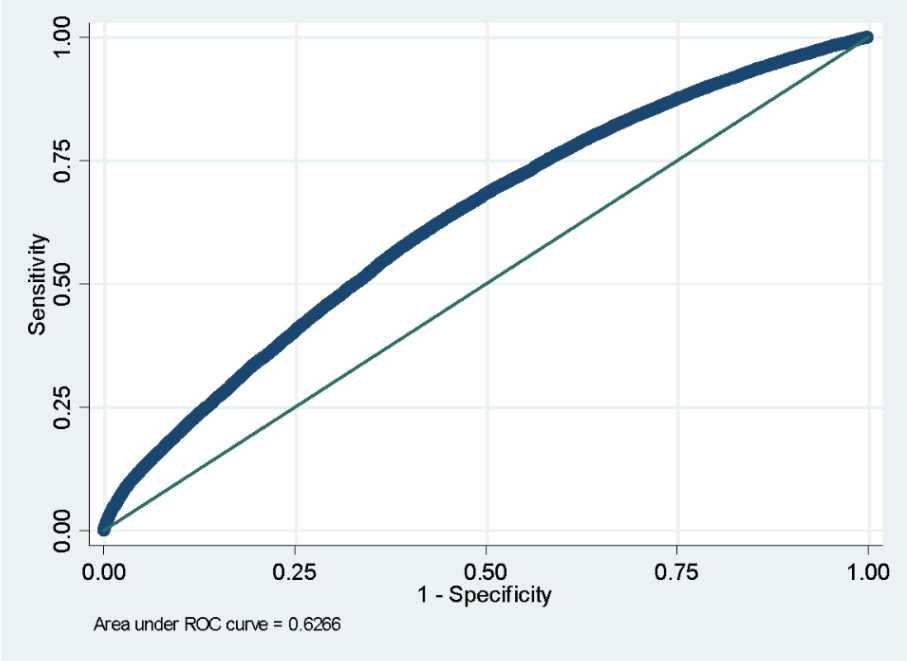
Baseline model + all 31 comorbidities



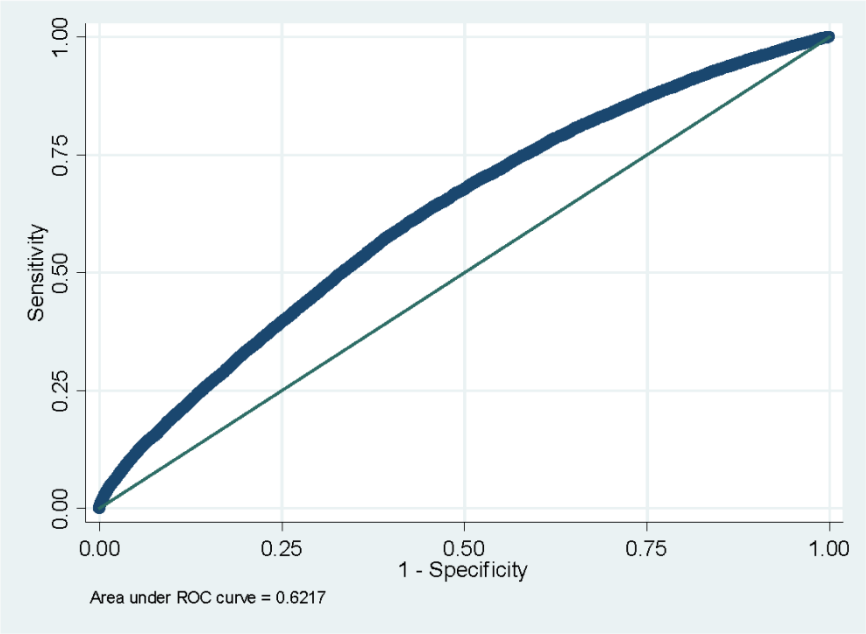
Baseline model + count of comorbidities



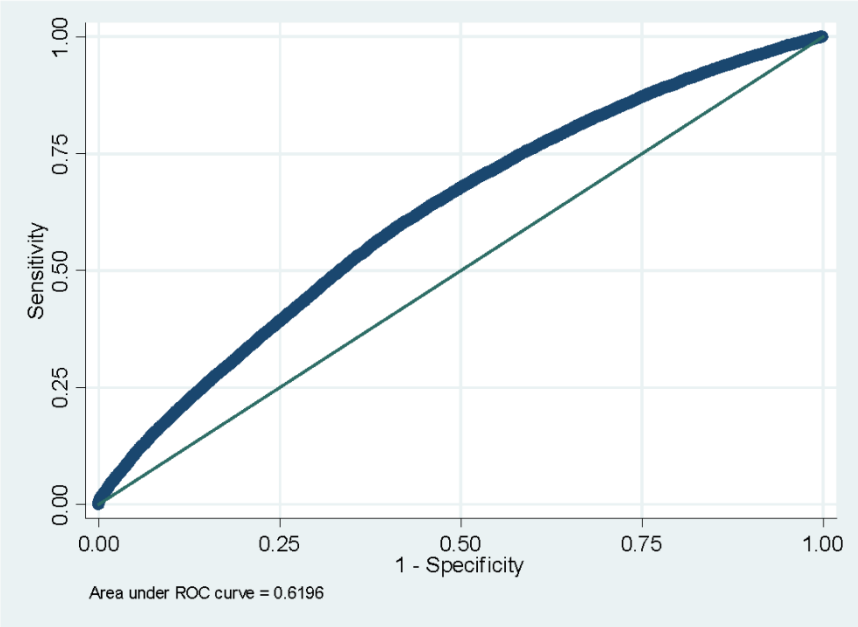
Baseline model + all 31 comorbidities



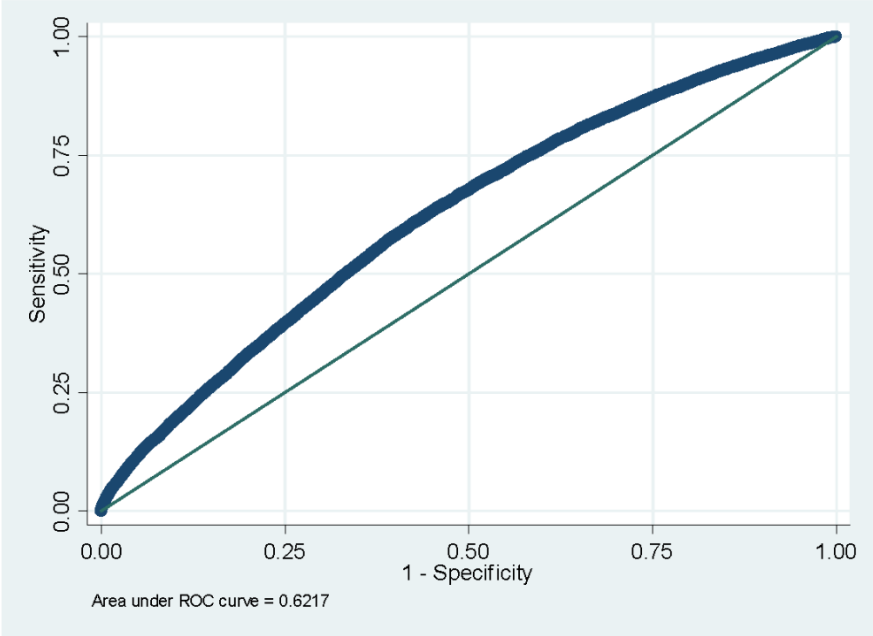
Baseline model + Charlson Comorbidity Index



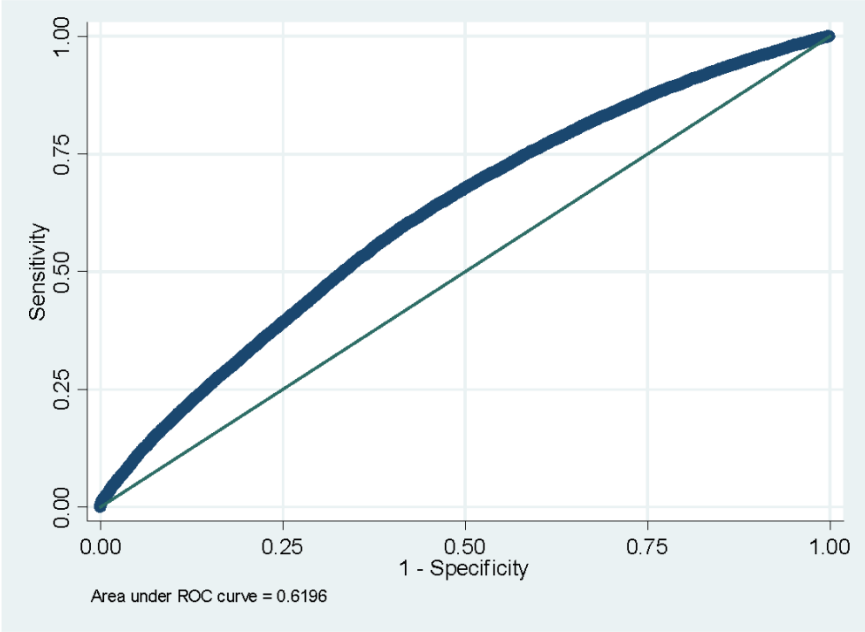
Baseline model + updated CCI per Quan et al. (2011)



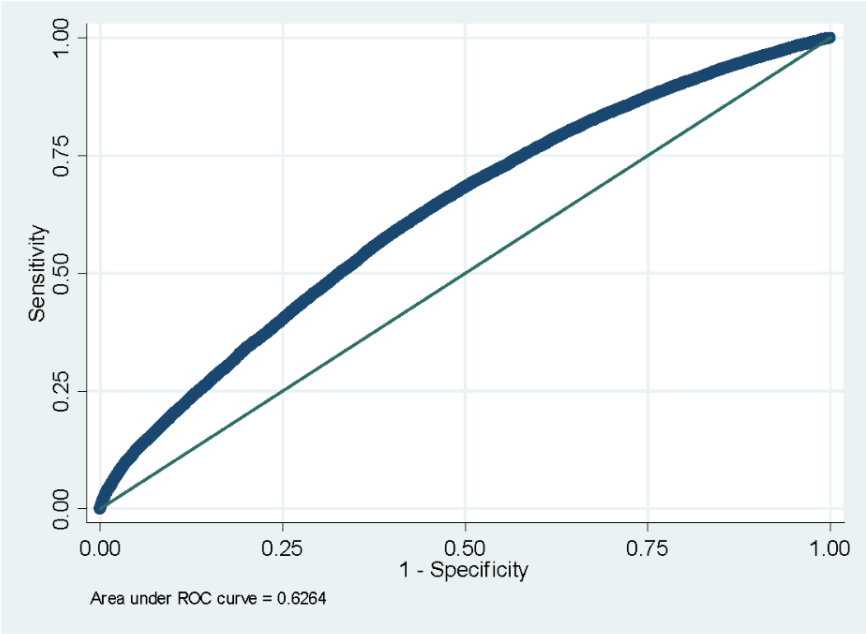
Baseline model + Charlson Comorbidity Index



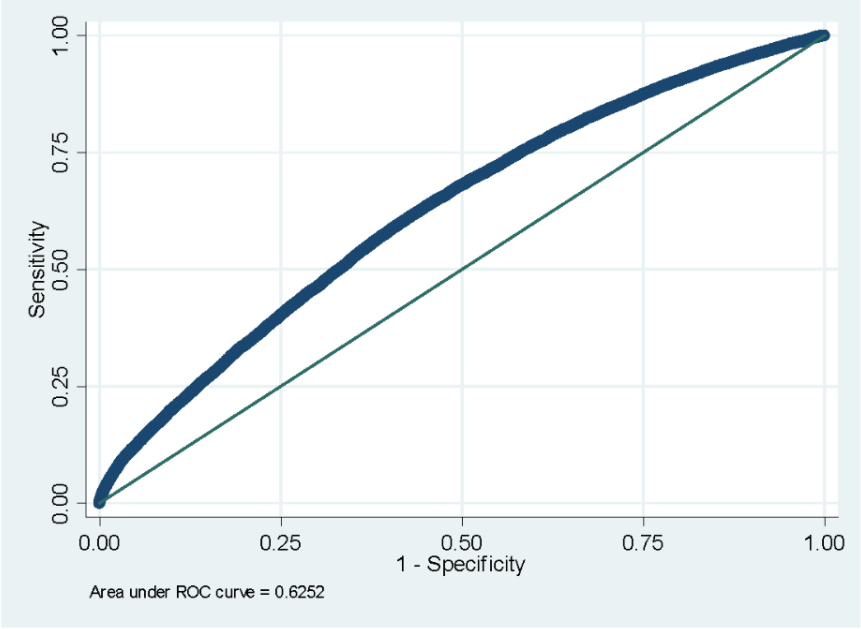
Baseline model + updated CCI per Quan et al. (2011)



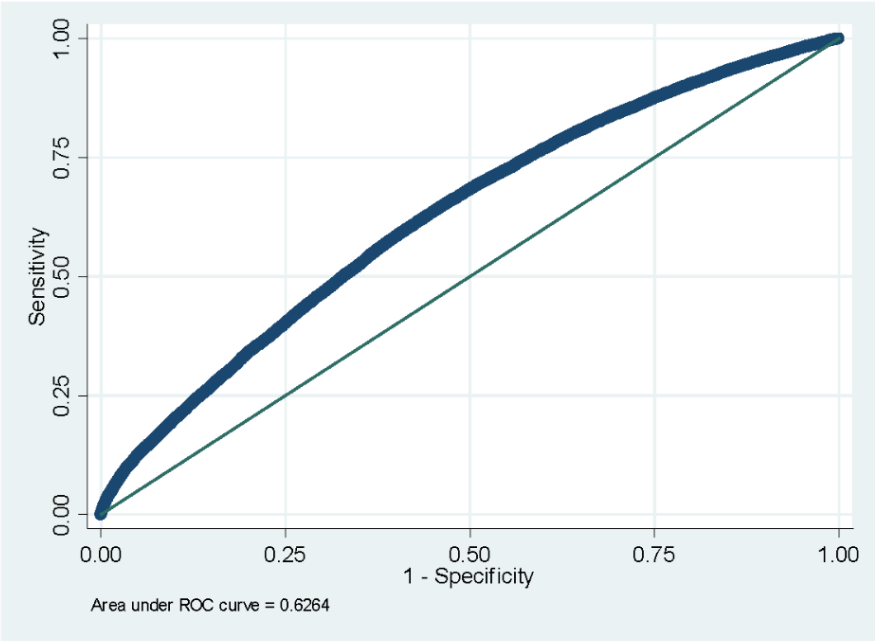
Baseline model + Elixhauser Comorbidity Measure



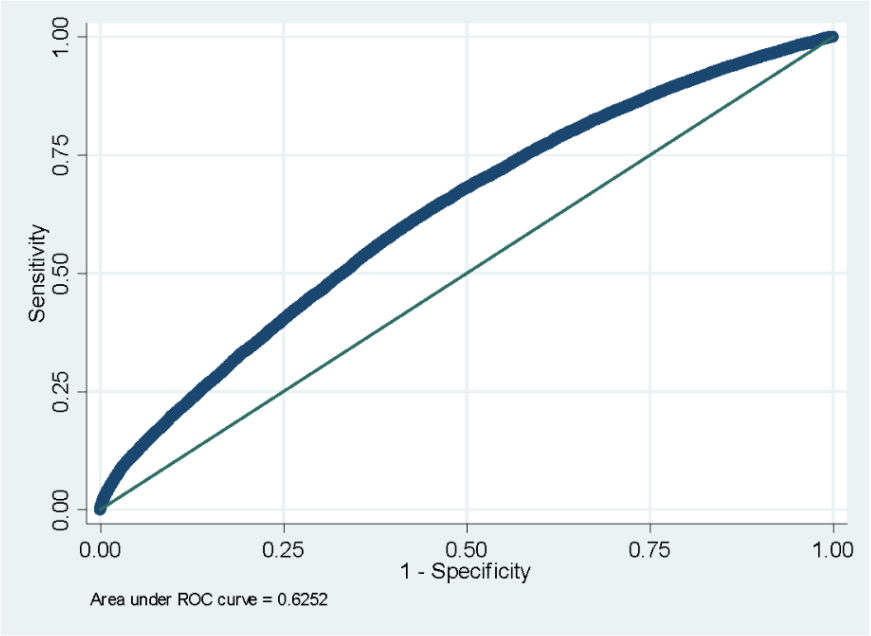
Baseline model + AICI-acr (10 conditions, binary representation)



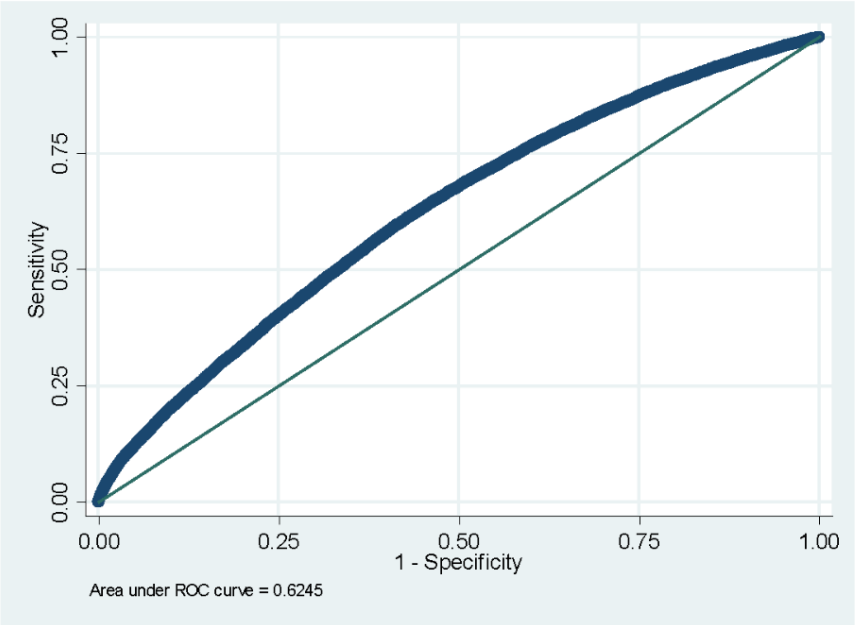
Baseline model + Elixhauser Comorbidity Measure



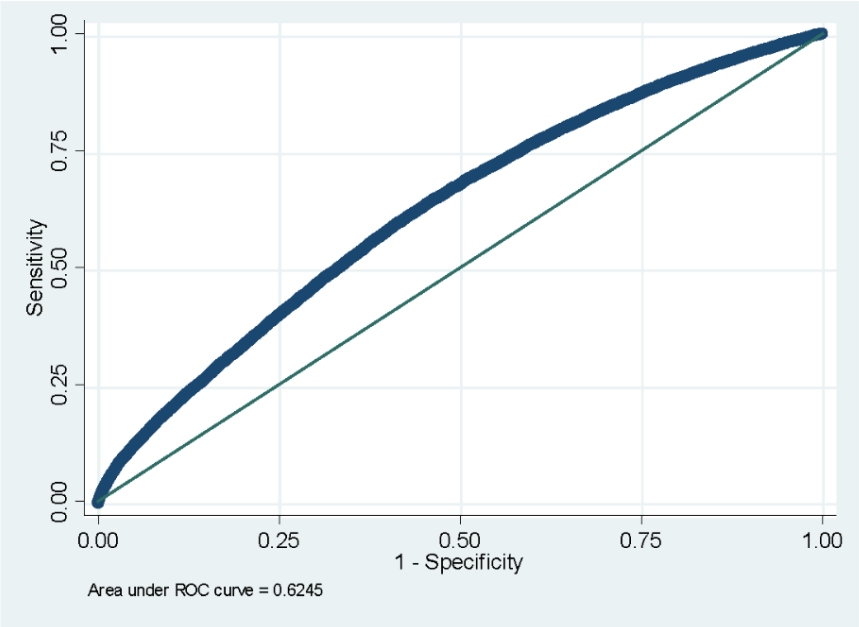
Baseline model + AICI-acr (10 conditions, binary representation)



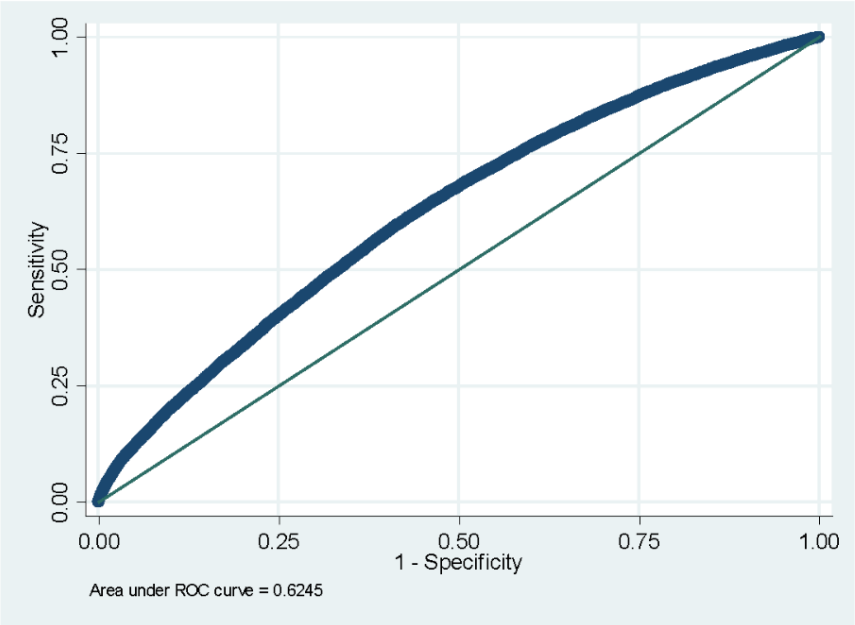
Baseline model + comorbidity index with actual weights (9 conditions)



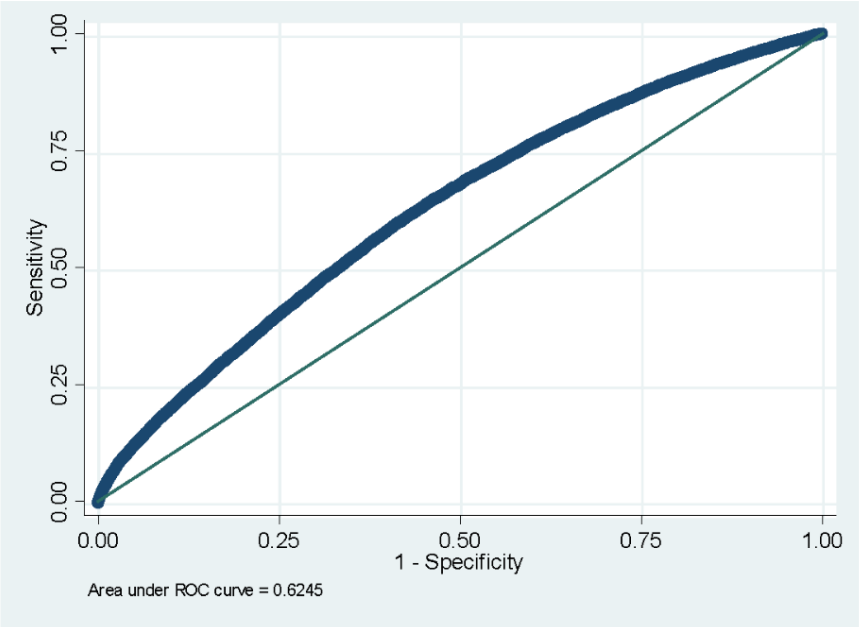
Baseline model + comorbidity index with rounded weights (9 conditions)



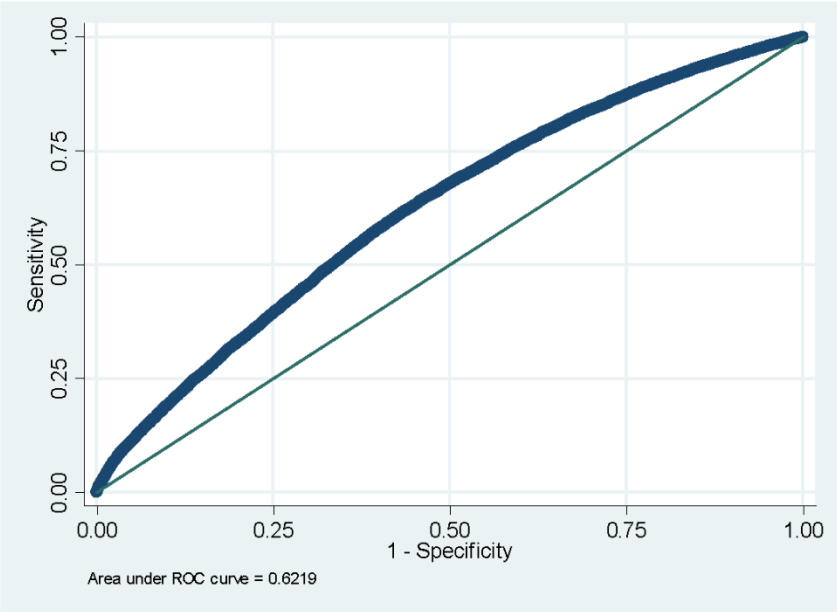
Baseline model + comorbidity index with actual weights (9 conditions)



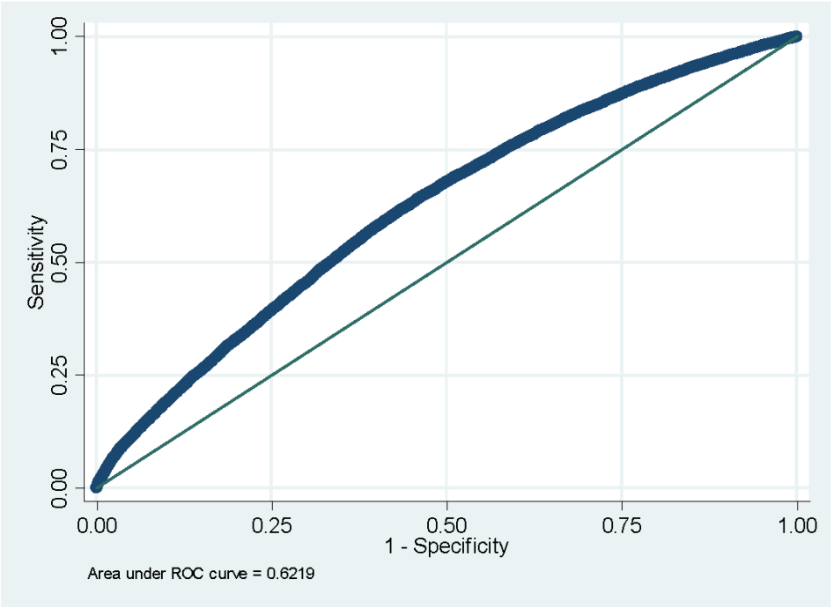
Baseline model + comorbidity index with rounded weights (9 conditions)



Baseline model + parsimonious index (8 conditions common to both readmission outcomes, binary representation)

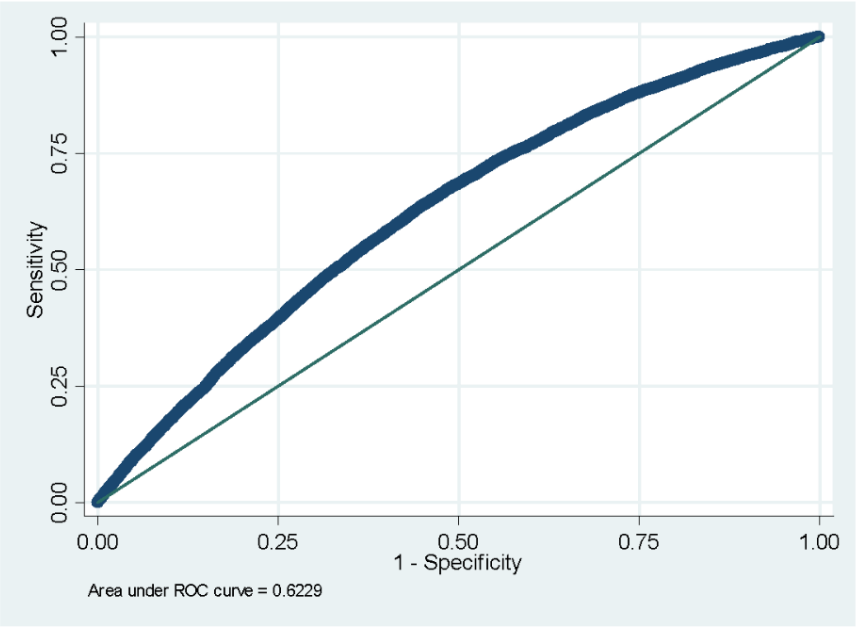


Baseline model + parsimonious index (8 conditions common to both readmission outcomes, binary representation)

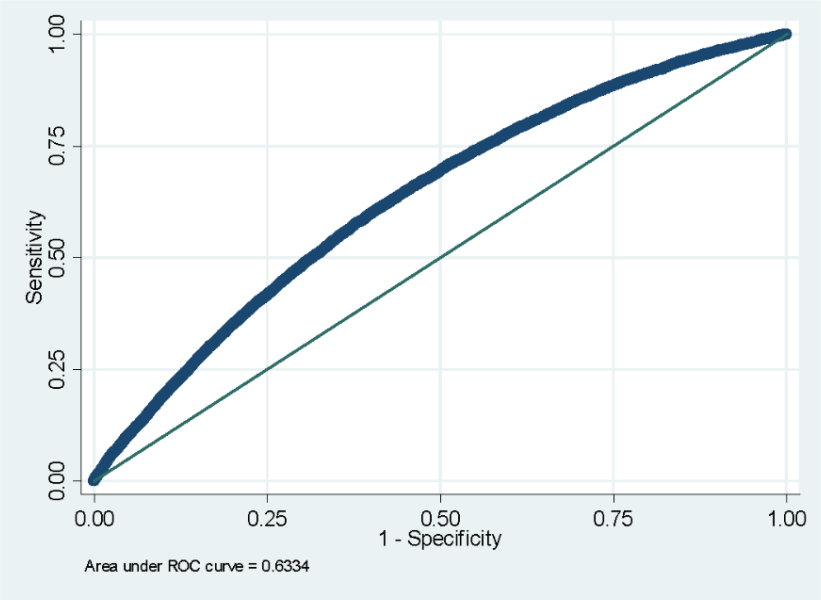


Appendix A1.5 – ROC curves for non-planned 30-day readmissions (age >= 15 years)

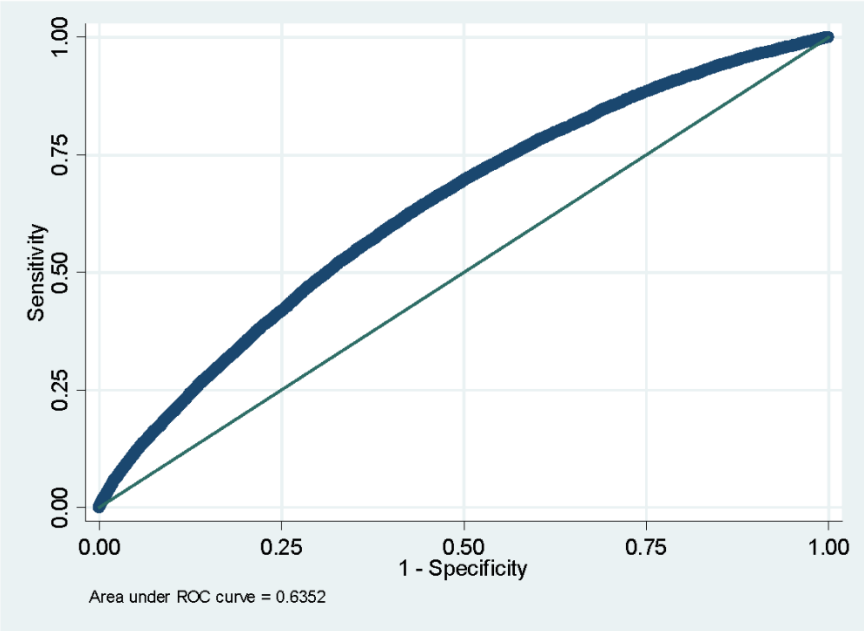
Baseline model (age, sex, body region, injury-type, injury-severity, geographic region and SEIFA)



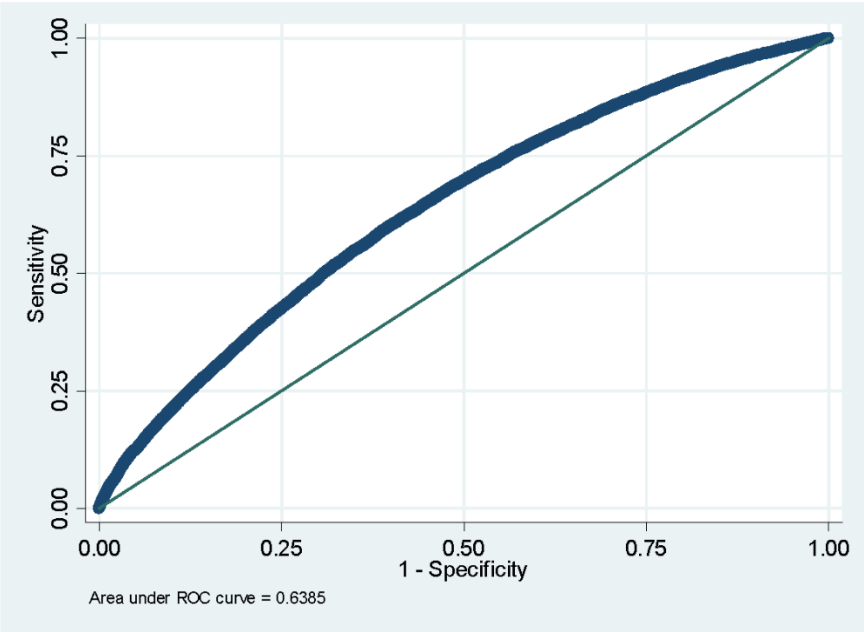
Baseline model + at least one comorbidity



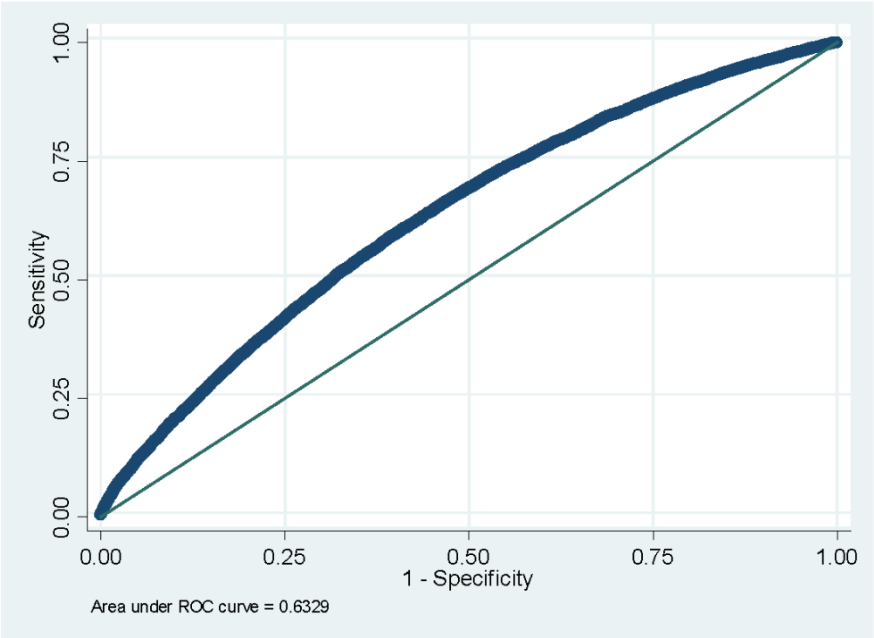
Baseline model + count of comorbidities



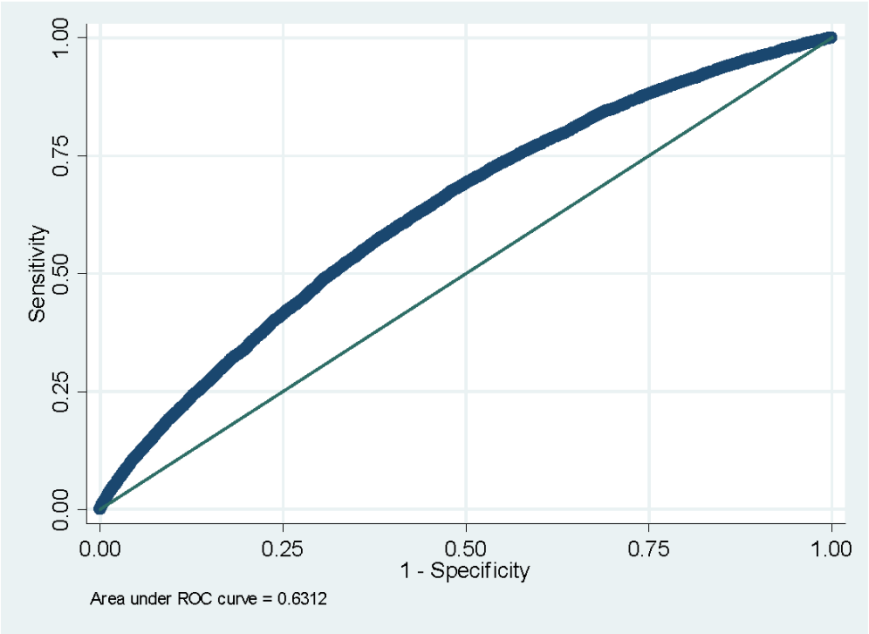
Baseline model + all 31 comorbidities



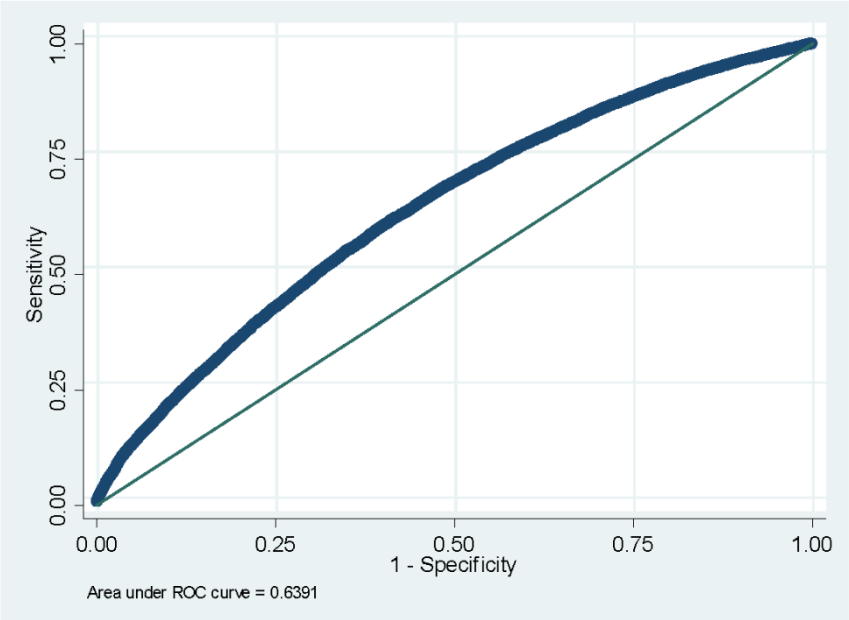
Baseline model + Charlson Comorbidity Index



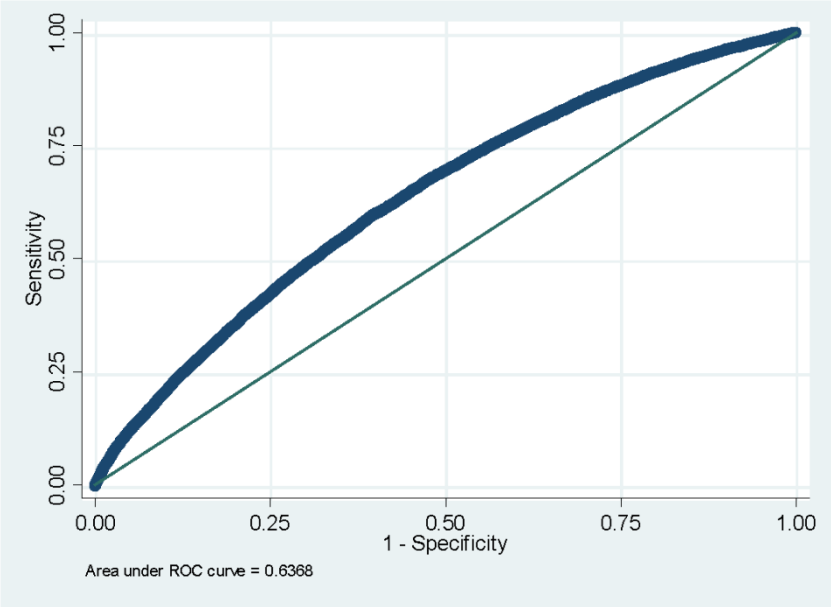
Baseline model + updated CCI per Quan et al. (2011)



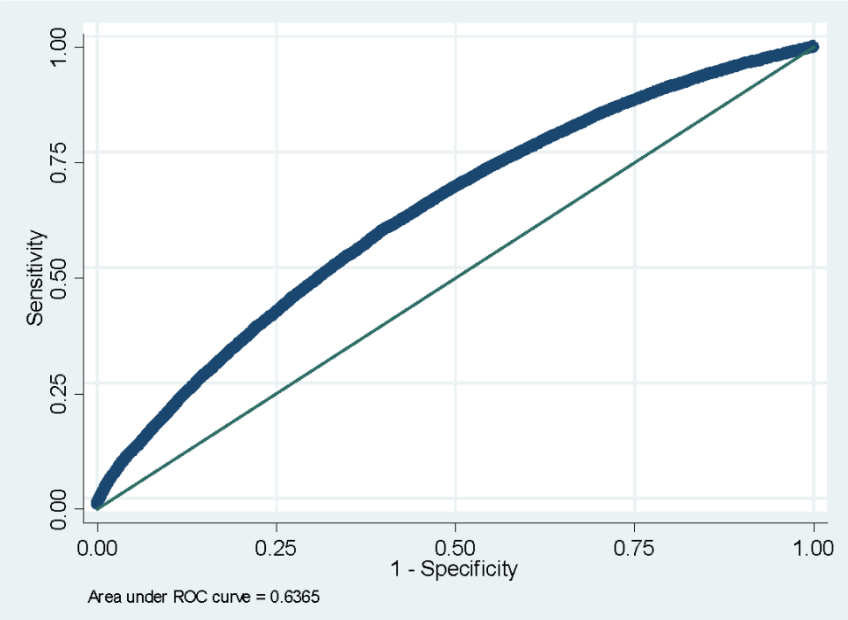
Baseline model + Elixhauser Comorbidity Measure



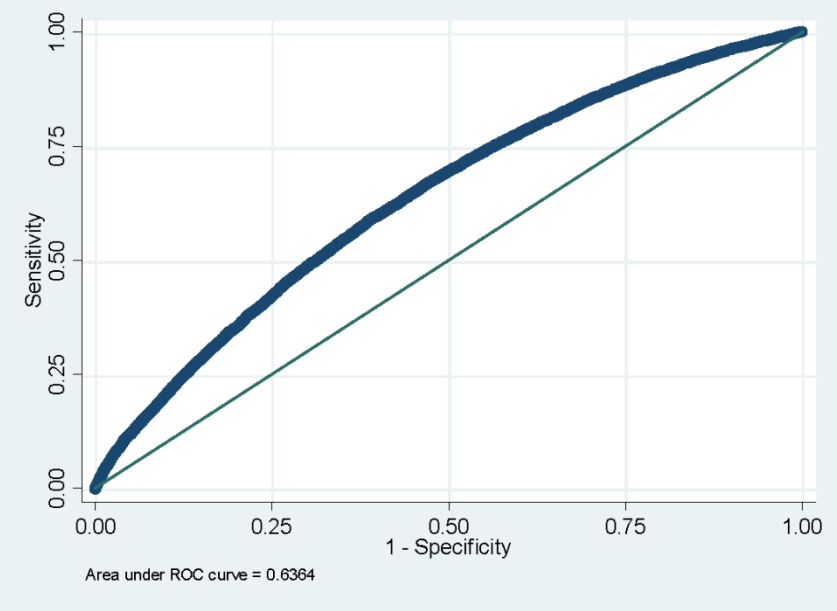
Baseline model + AICI-npr (11 conditions, binary representation)



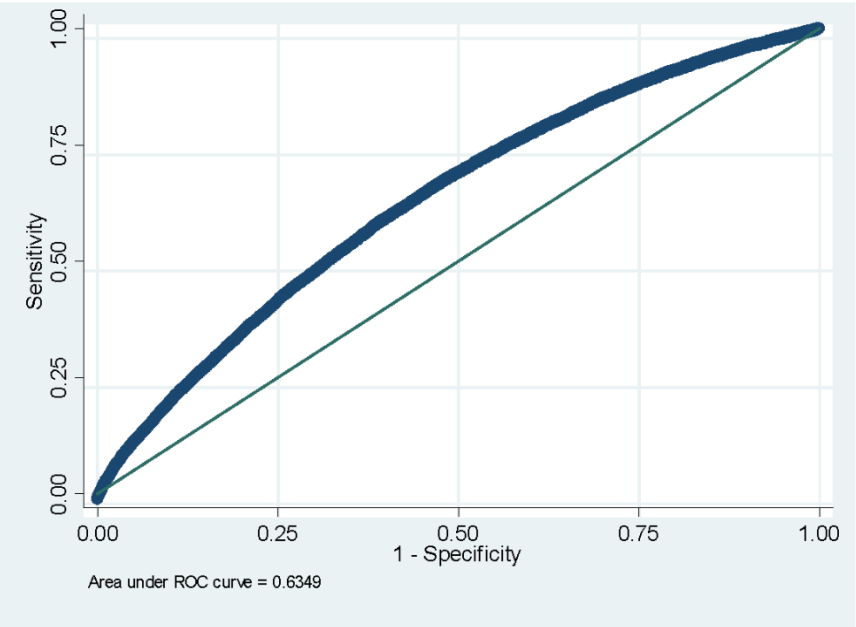
Baseline model + comorbidity index with actual weights (11 conditions)



Baseline model + comorbidity index with rounded weights (11 conditions)

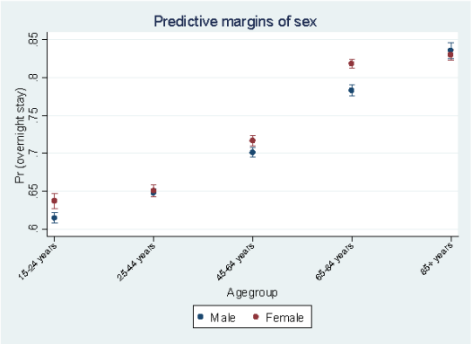


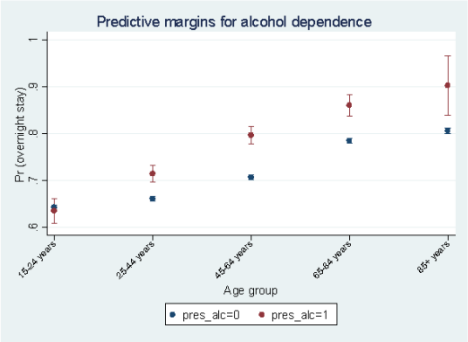
Baseline model + parsimonious index (8 conditions common to both readmission outcomes, binary representation)

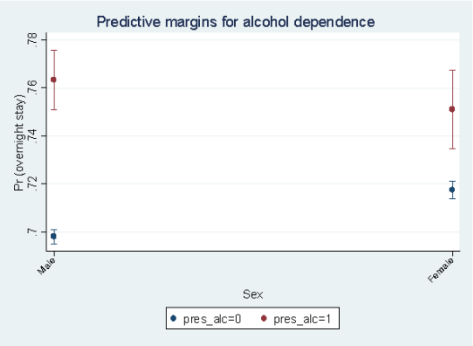


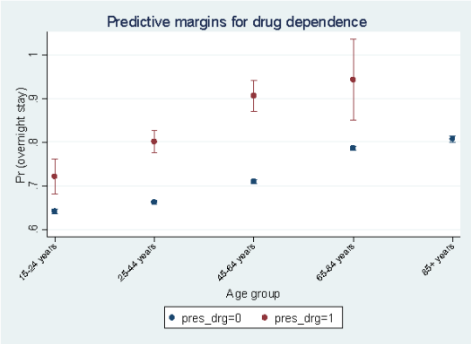
Appendix A2 – Interaction plots

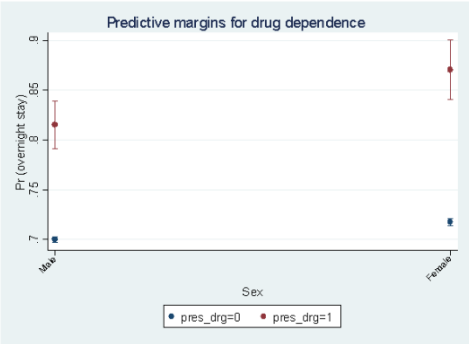
Overnight stay

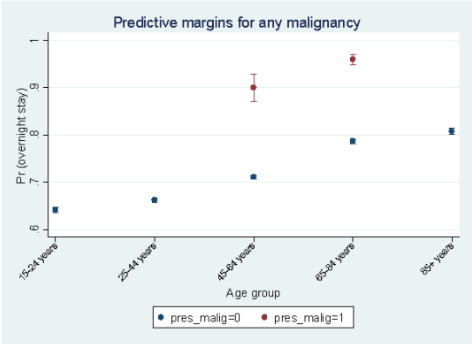


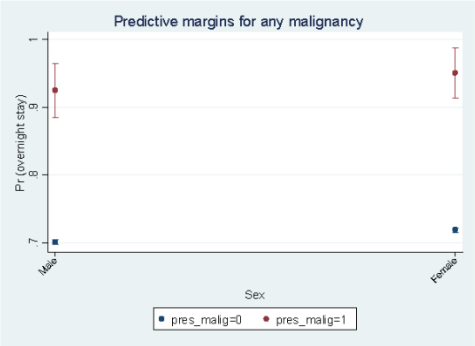


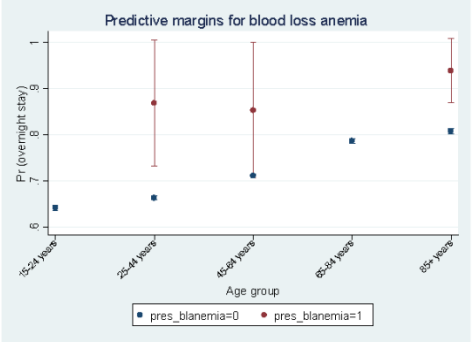


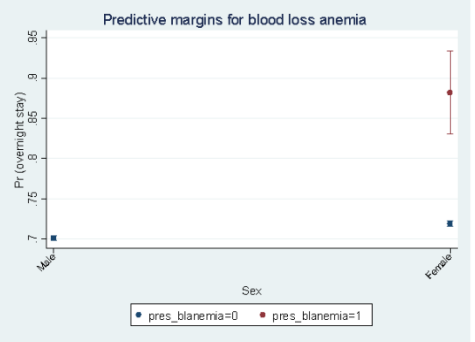


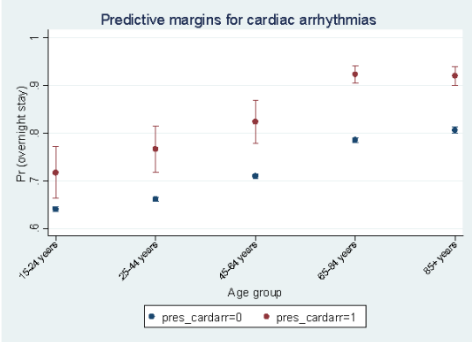


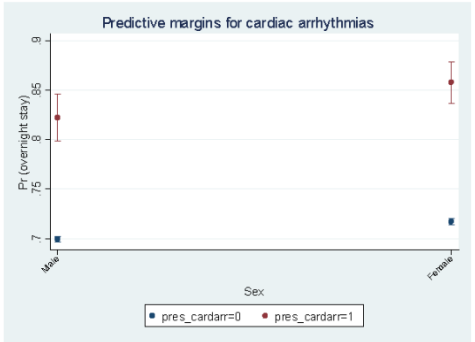

Predictive margins for any malignancy
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_malig=0
pres_malig=1

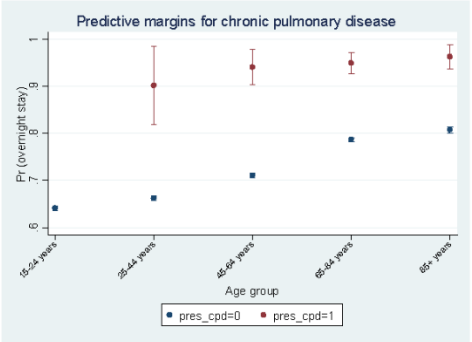

Predictive margins for any malignancy
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_malig=0
pres_malig=1

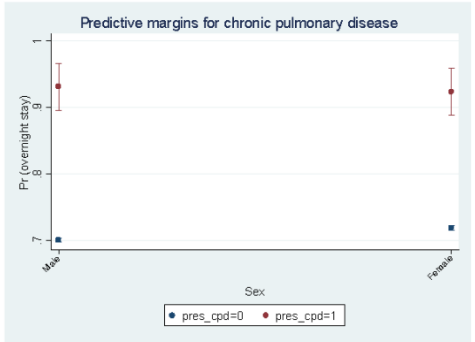

Predictive margins for blood loss anemia
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_blanemia=0
pres_blanemia=1

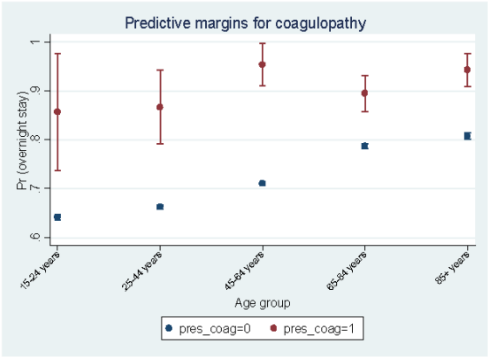

Predictive margins for blood loss anemia
Pr (overnight stay)
.7
.75
.8
.85
.9
.95
Male
Female
Sex
pres_blanemia=0
pres_blanemia=1

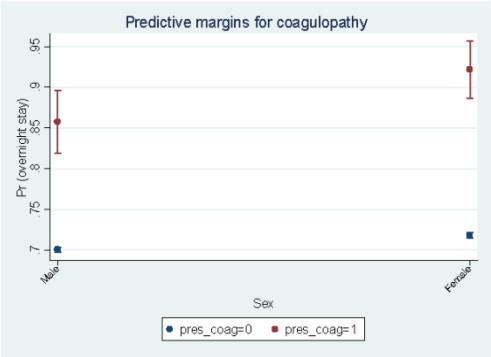

Predictive margins for cardiac arrhythmias
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cardarr=0
pres_cardarr=1

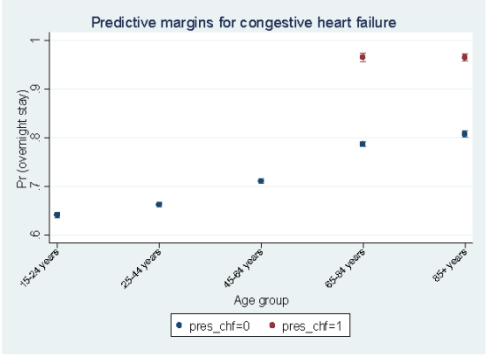

Predictive margins for cardiac arrhythmias
Pr (overnight stay)
.7
.75
.8
.85
.9
Male
Female
Sex
pres_cardarr=0
pres_cardarr=1

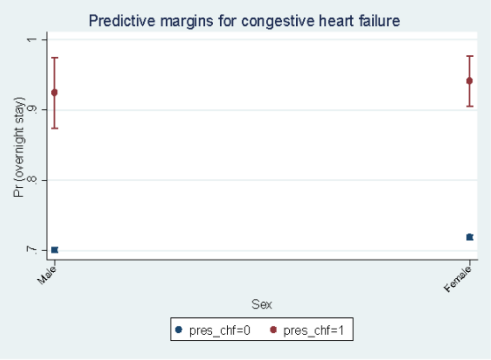

Predictive margins for chronic pulmonary disease
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

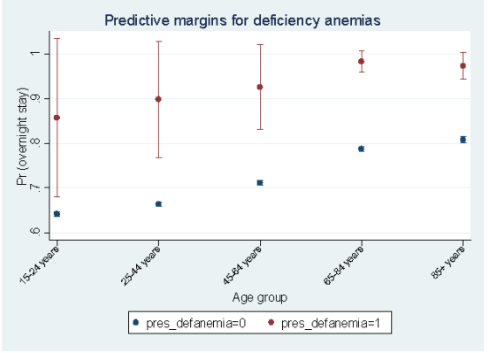

Predictive margins for chronic pulmonary disease
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_cpd=0
pres_cpd=1

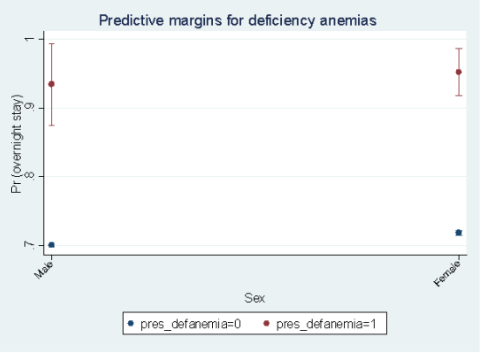

Predictive margins for coagulopathy
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

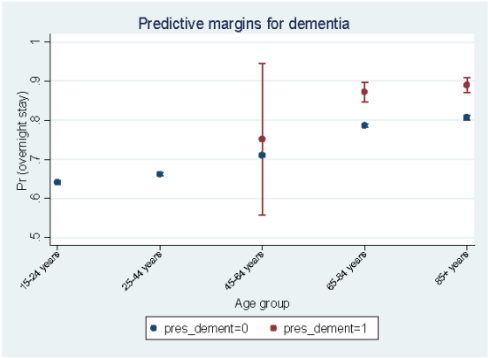

Predictive margins for coagulopathy
Pr (overnight stay)
.7
.75
.8
.85
.9
.95
Male
Female
Sex
pres_coag=0
pres_coag=1

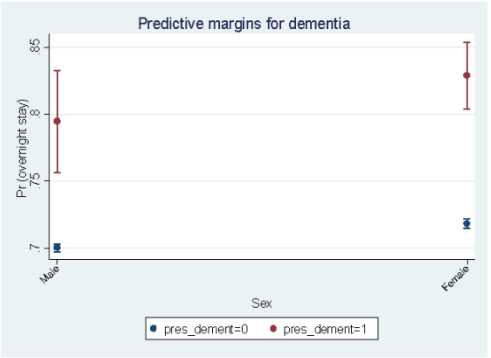

Predictive margins for congestive heart failure
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

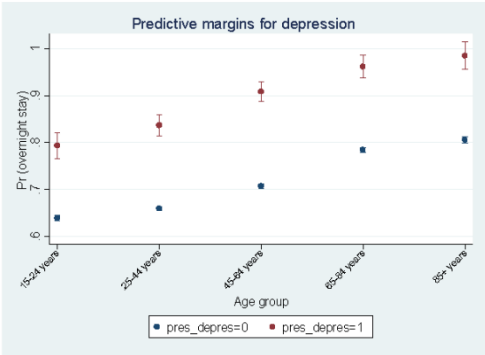

Predictive margins for congestive heart failure
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_chf=0
pres_chf=1

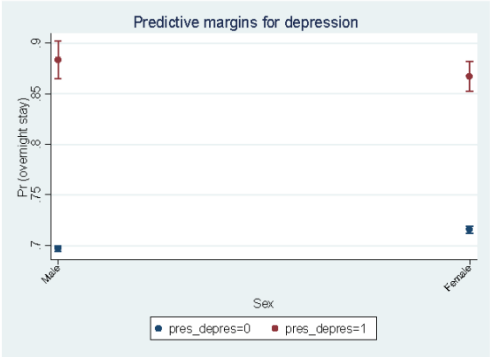

Predictive margins for deficiency anemias
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_defanemia=0
pres_defanemia=1

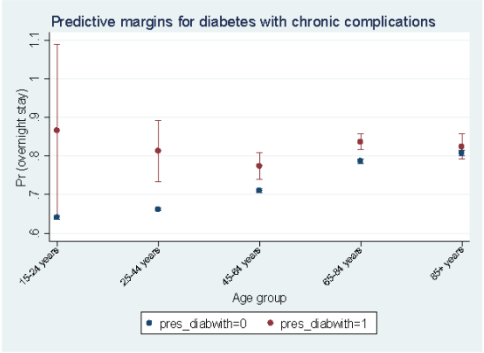

Predictive margins for deficiency anemias
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_defanemia=0
pres_defanemia=1

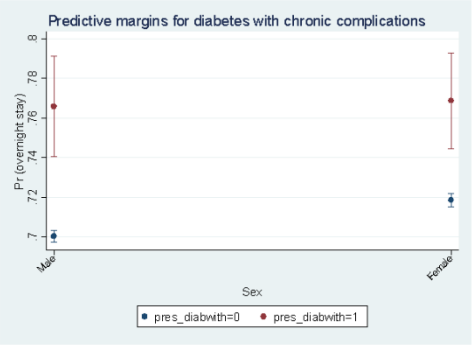

Predictive margins for dementia
Pr (overnight stay)
.5
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1

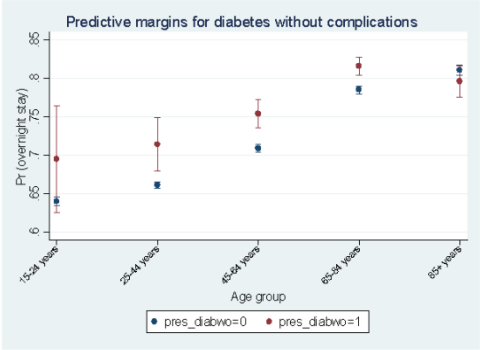

Predictive margins for dementia
Pr (overnight stay)
.7
.75
.8
.85
Male
Female
Sex
pres_dement=0
pres_dement=1

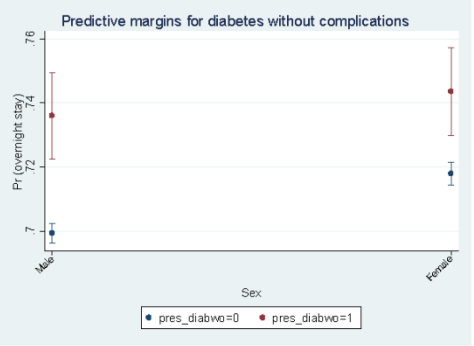

Predictive margins for depression
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_depres=0
pres_depres=1

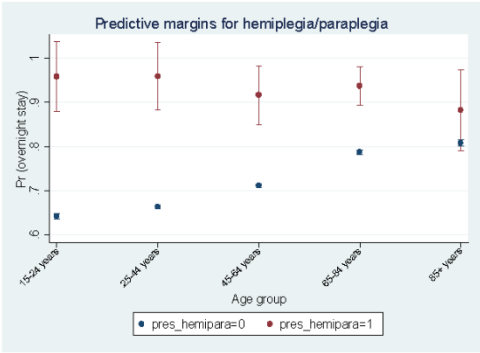

Predictive margins for depression
Pr (overnight stay)
.7
.75
.8
.85
.9
Male
Female
Sex
pres_depres=0
pres_depres=1

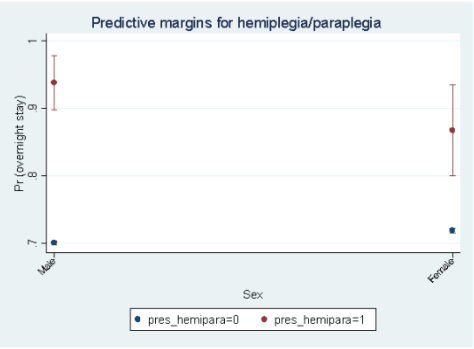

Predictive margins for diabetes with chronic complications
Pr (overnight stay)
.6
.7
.8
.9
1
1.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

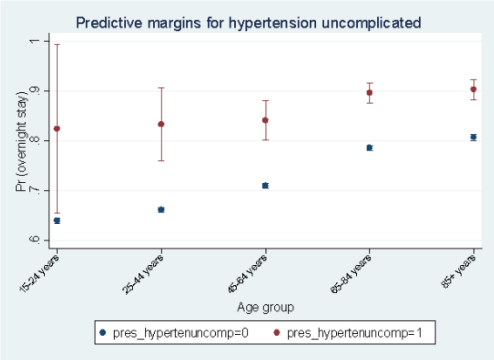

Predictive margins for diabetes with chronic complications
Pr (overnight stay)
.7
.72
.74
.76
.78
.8
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

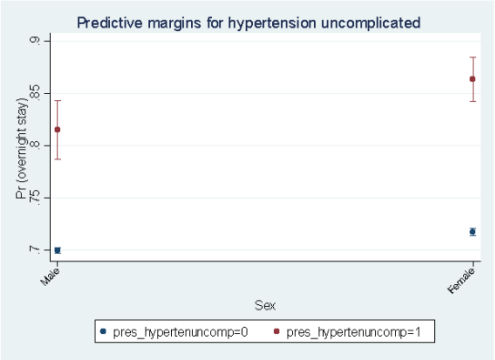

Predictive margins for diabetes without complications
Pr (overnight stay)
.6
.65
.7
.75
.8
.85
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

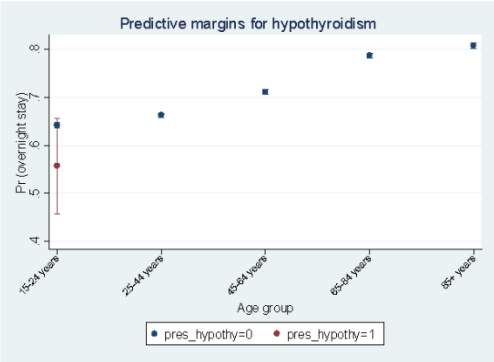

Predictive margins for diabetes without complications
Pr (overnight stay)
.7
.72
.74
.76
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

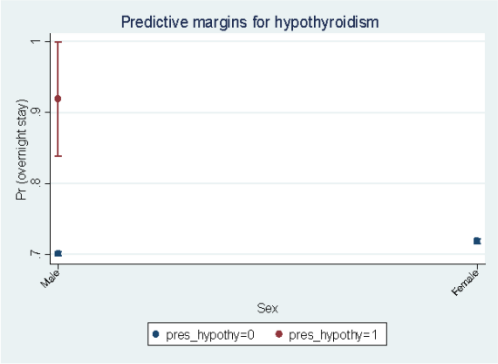

Predictive margins for hemiplegia/paraplegia
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hemipara=0
pres_hemipara=1

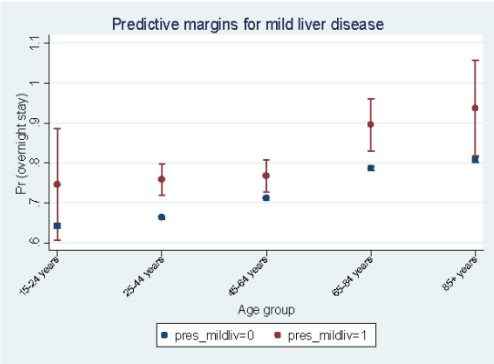

Predictive margins for hemiplegia/paraplegia
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_hemipara=0
pres_hemipara=1

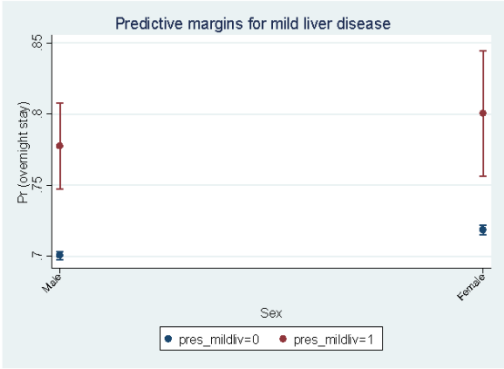

Predictive margins for hypertension uncomplicated
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypertenuncomp=0
pres_hypertenuncomp=1

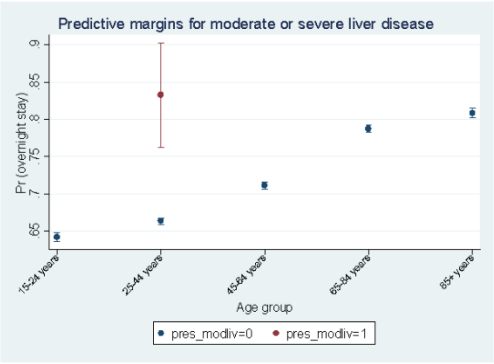

Predictive margins for hypertension uncomplicated
Pr (overnight stay)
.7
.75
.8
.85
.9
Male
Female
Sex
pres_hypertenuncomp=0
pres_hypertenuncomp=1

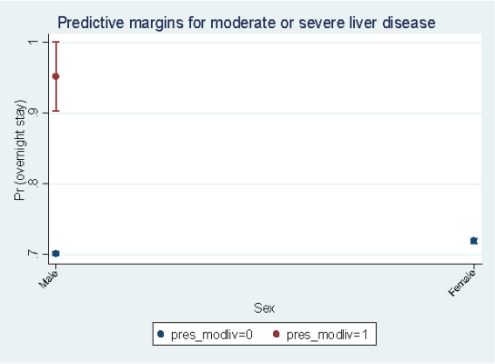

Predictive margins for hypothyroidism
Pr (overnight stay)
.4
.5
.6
.7
.8
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypothy=0
pres_hypothy=1

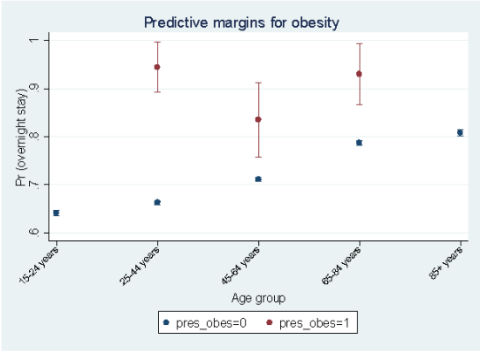

Predictive margins for hypothyroidism
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_hypothy=0
pres_hypothy=1


Predictive margins for mild liver disease
Pr (overnight stay)
.6
.7
.8
.9
1
1.1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1

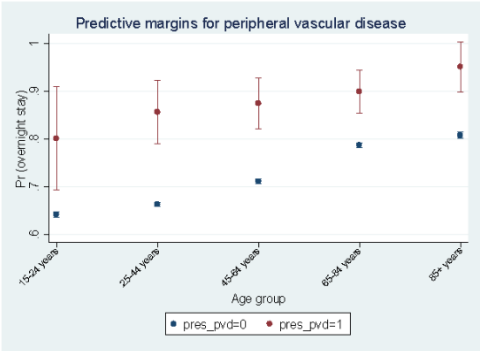

Predictive margins for mild liver disease
Pr (overnight stay)
.7
.75
.8
.85
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

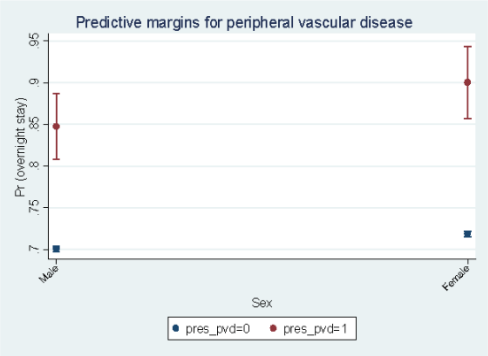

Predictive margins for moderate or severe liver disease
Pr (overnight stay)
.65
.7
.75
.8
.85
.9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_modliv=0
pres_modliv=1

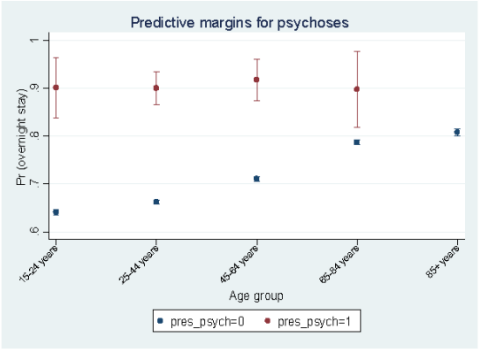

Predictive margins for moderate or severe liver disease
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_modliv=0
pres_modliv=1

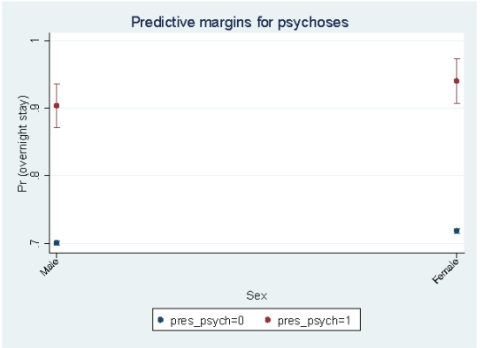

Predictive margins for obesity
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_obes=0
pres_obes=1

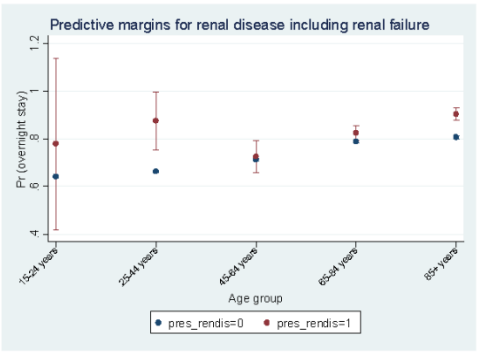

Predictive margins for obesity
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_obes=0
pres_obes=1

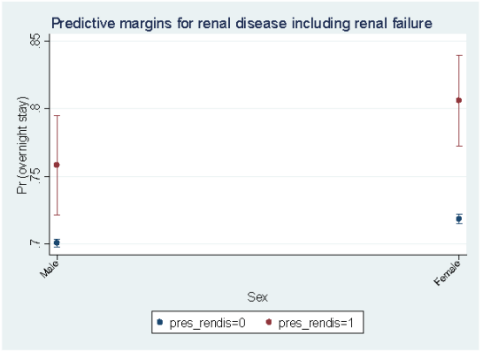

Predictive margins for peripheral vascular disease
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pvd=0
pres_pvd=1

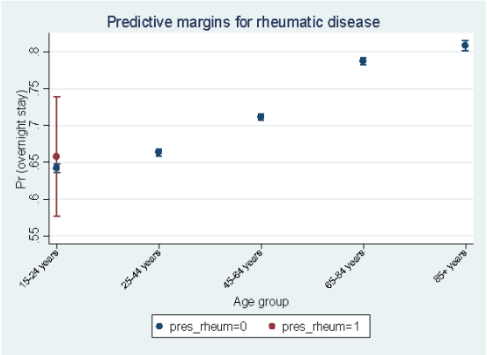

Predictive margins for peripheral vascular disease
Pr (overnight stay)
.7
.75
.8
.85
.9
.95
Male
Female
Sex
pres_pvd=0
pres_pvd=1

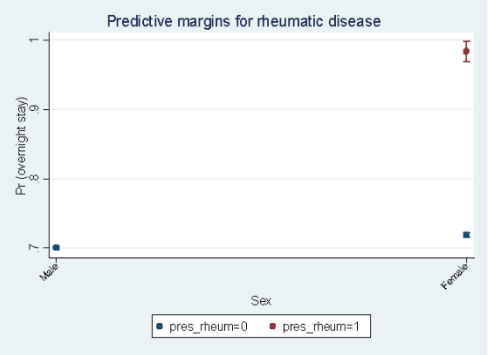

Predictive margins for psychoses
Pr (overnight stay)
.6
.7
.8
.9
1
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_psych=0
pres_psych=1

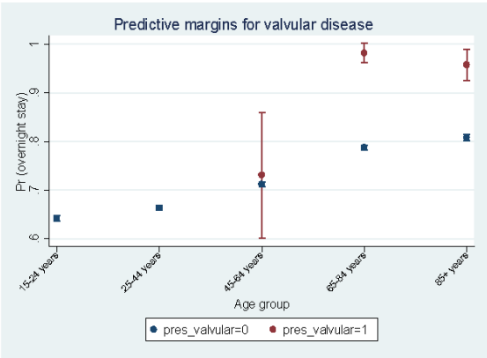

Predictive margins for psychoses
Pr (overnight stay)
.7
.8
.9
1
Male
Female
Sex
pres_psych=0
pres_psych=1

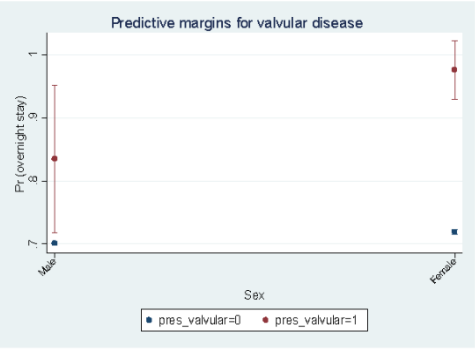

Predictive margins for renal disease including renal failure
Pr (overnight stay)
.4
.6
.8
1
1.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rendis=0
pres_rendis=1


Predictive margins for renal disease including renal failure
Pr (overnight stay)
.7
.75
.8
.85
Male
Female
Sex
pres_rendis=0
pres_rendis=1

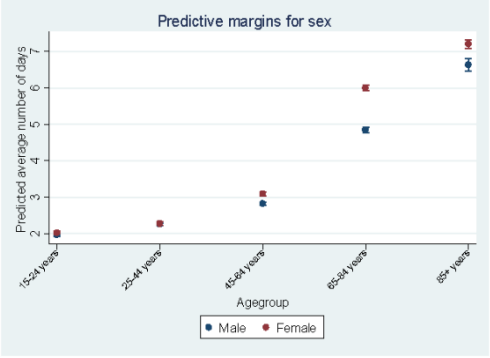


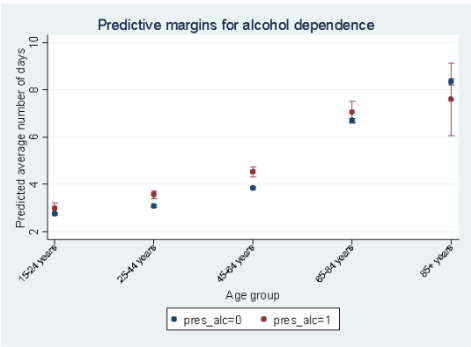


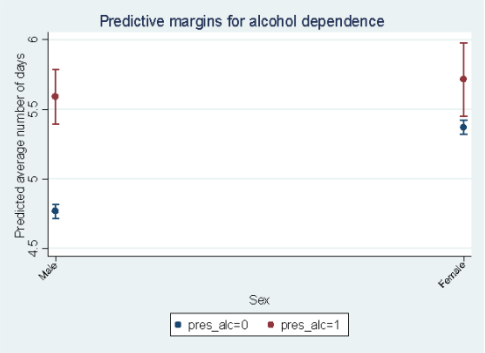


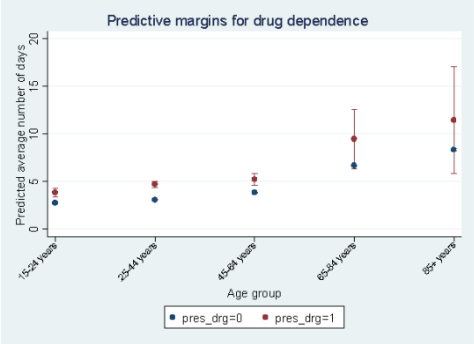


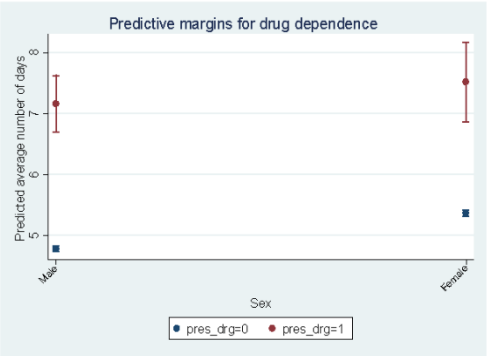
1<=Length of stay<=30 days

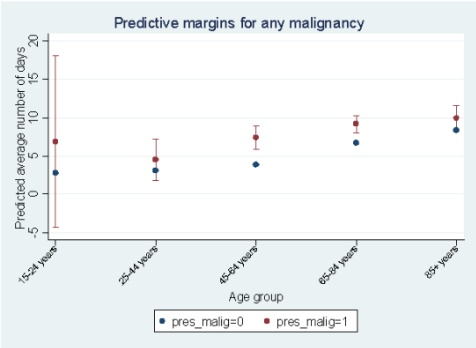


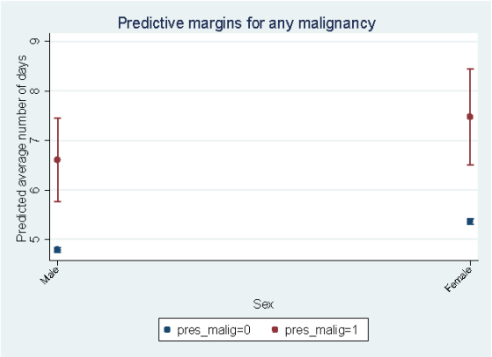

Predictive margins for alcohol dependence
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_alc=0
pres_alc=1

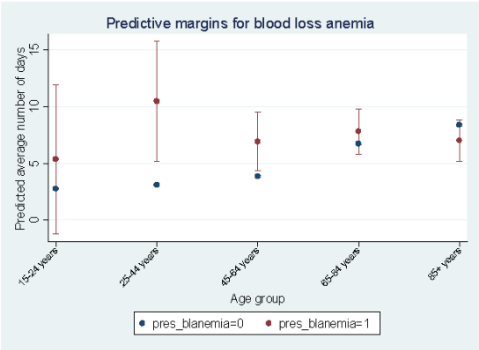

Predictive margins for alcohol dependence
Predicted average number of days
4.5
5
5.5
6
Male
Female
Sex
pres_alc=0
pres_alc=1

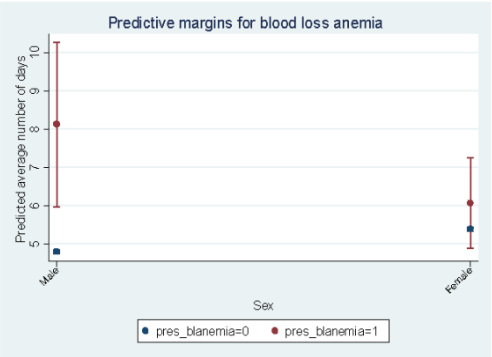

Predictive margins for drug dependence
Predicted average number of days
0
5
10
15
20
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_drg=0
pres_drg=1

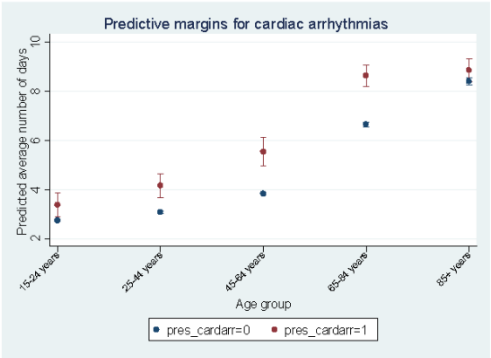

Predictive margins for drug dependence
Predicted average number of days
5
6
7
8
Male
Female
Sex
pres_drg=0
pres_drg=1

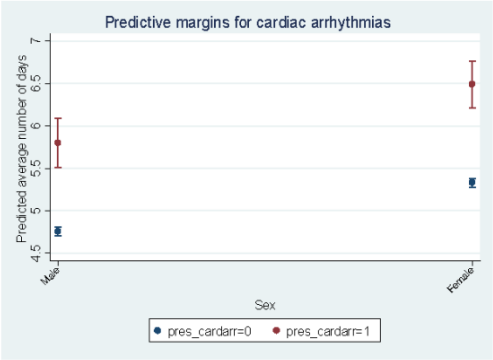

Predictive margins for any malignancy
Predicted average number of days
-5
0
5
10
15
20
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_malig=0
pres_malig=1

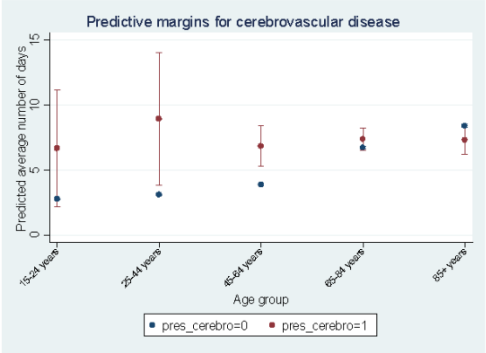

Predictive margins for any malignancy
Predicted average number of days
5
6
7
8
9
Male
Female
Sex
pres_malig=0
pres_malig=1

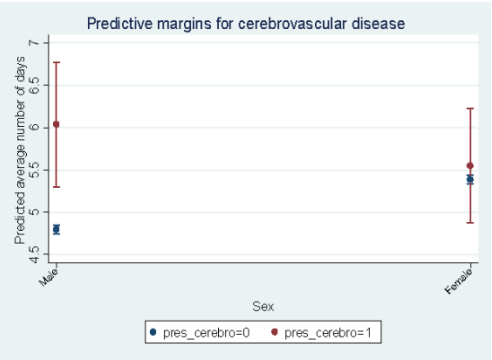

Predictive margins for blood loss anemia
Predicted average number of days
0
5
10
15
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_blanemia=0
pres_blanemia=1

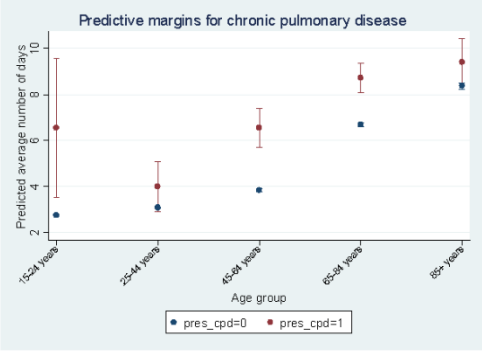

Predictive margins for blood loss anemia
Predicted average number of days
5
6
7
8
9
10
Male
Female
Sex
pres_blanemia=0
pres_blanemia=1

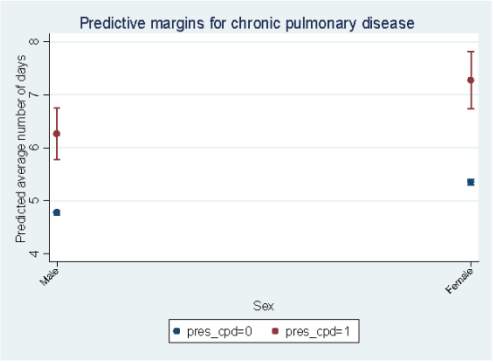

Predictive margins for cardiac arrhythmias
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cardarr=0
pres_cardarr=1

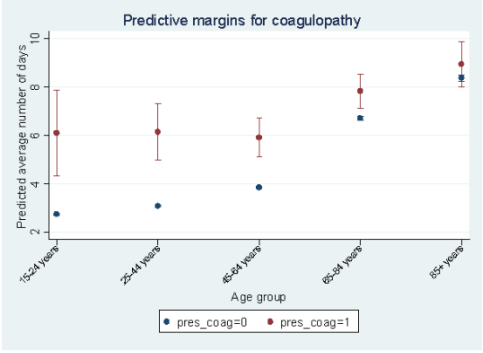

Predictive margins for cardiac arrhythmias
Predicted average number of days
4.5
5
5.5
6
6.5
7
Male
Female
Sex
pres_cardarr=0
pres_cardarr=1

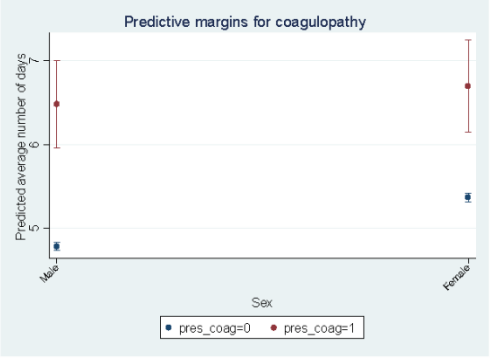

Predictive margins for cerebrovascular disease
Predicted average number of days
0
5
10
15
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cerebro=0
pres_cerebro=1

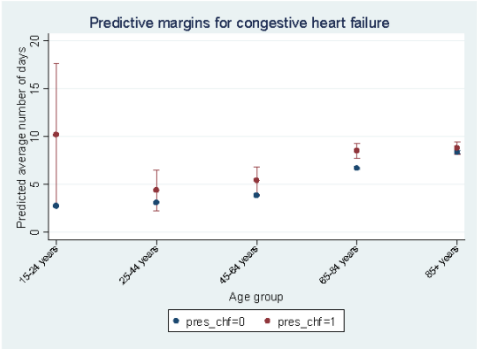

Predictive margins for cerebrovascular disease
Predicted average number of days
4.5
5
5.5
6
6.5
7
Male
Female
Sex
pres_cerebro=0
pres_cerebro=1

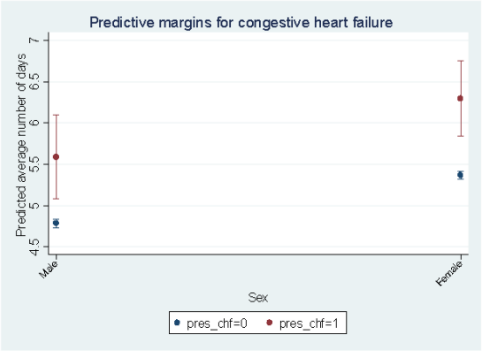

Predictive margins for chronic pulmonary disease
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

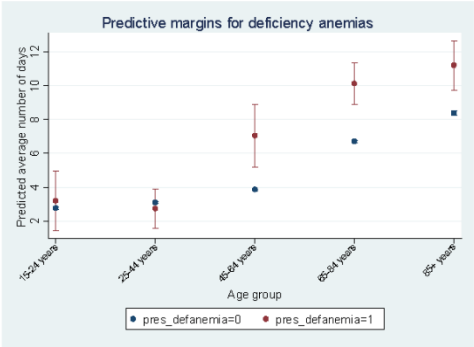

Predictive margins for chronic pulmonary disease
Predicted average number of days
4
5
6
7
8
Male
Female
Sex
pres_cpd=0
pres_cpd=1

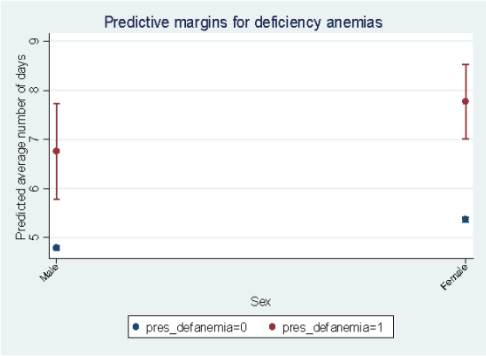

Predictive margins for coagulopathy
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

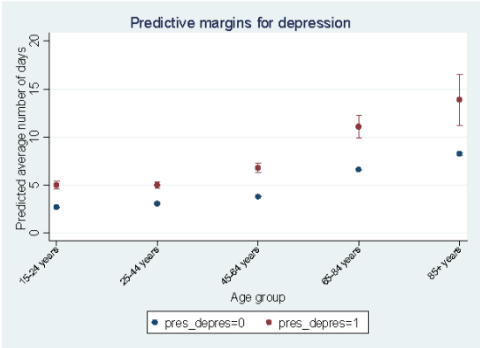

Predictive margins for coagulopathy
Predicted average number of days
5
6
7
Male
Female
Sex
pres_coag=0
pres_coag=1

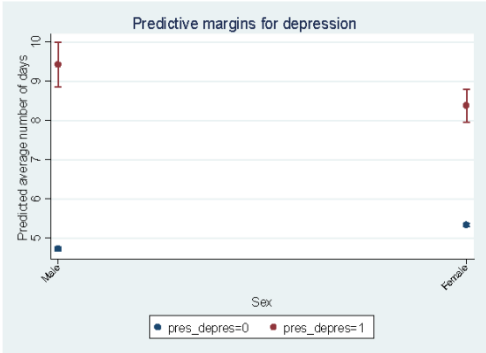

Predictive margins for congestive heart failure
Predicted average number of days
0
5
10
15
20
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

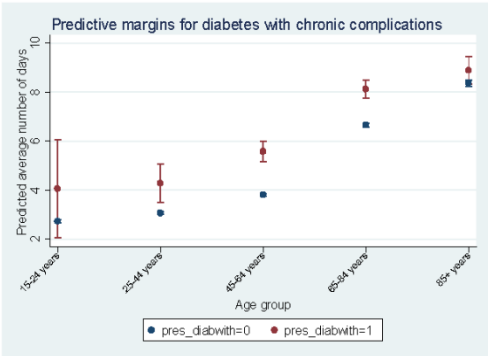

Predictive margins for congestive heart failure
Predicted average number of days
4.5
5
5.5
6
6.5
7
Male
Female
Sex
pres_chf=0
pres_chf=1

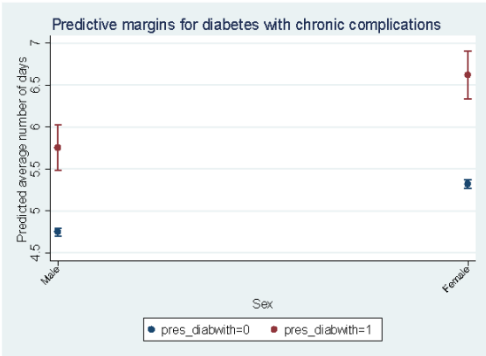

Predictive margins for deficiency anemias
Predicted average number of days
2
4
6
8
10
12
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_defanemia=0
pres_defanemia=1

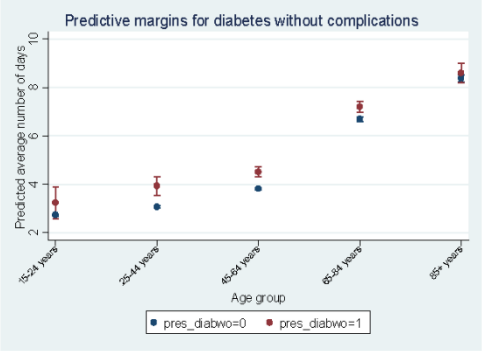

Predictive margins for deficiency anemias
Predicted average number of days
5
6
7
8
9
Male
Female
Sex
pres_defanemia=0
pres_defanemia=1

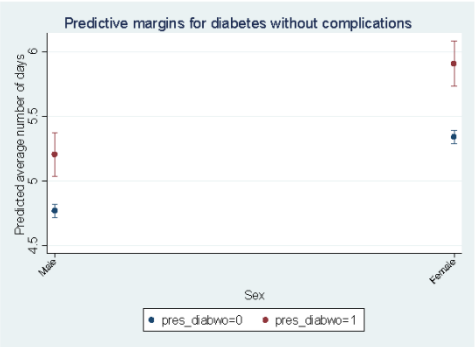

Predictive margins for depression
Predicted average number of days
0
5
10
15
20
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_depres=0
pres_depres=1

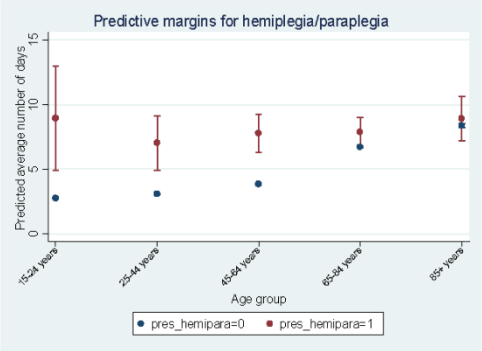

Predictive margins for depression
Predicted average number of days
5
6
7
8
9
10
Male
Female
Sex
pres_depres=0
pres_depres=1

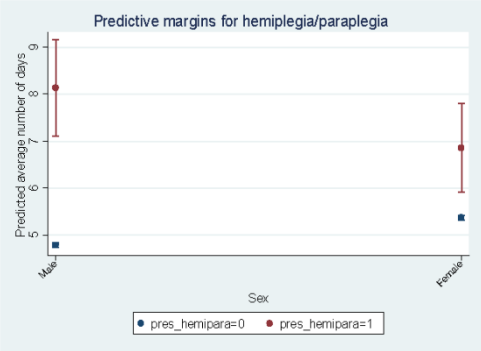

Predictive margins for diabetes with chronic complications
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

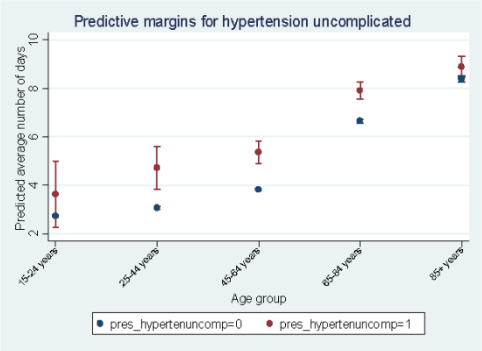

Predictive margins for diabetes with chronic complications
Predicted average number of days
4.5
5
5.5
6
6.5
7
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

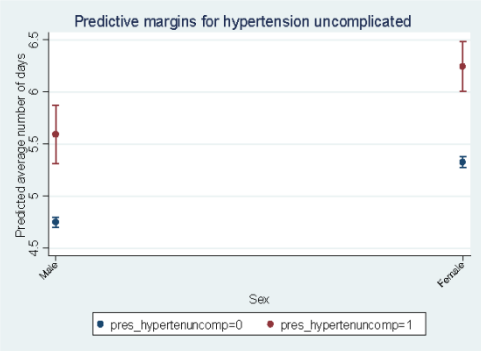

Predictive margins for diabetes without complications
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

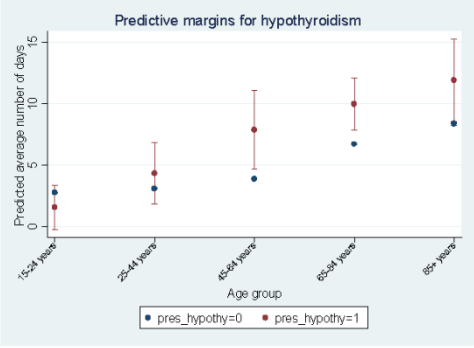

Predictive margins for diabetes without complications
Predicted average number of days
4.5
5
5.5
6
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

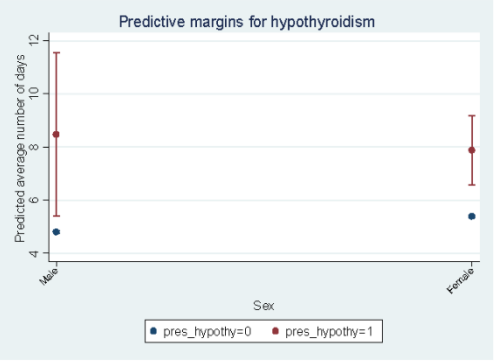

Predictive margins for hemiplegia/paraplegia
Predicted average number of days
0
5
10
15
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hemipara=0
pres_hemipara=1

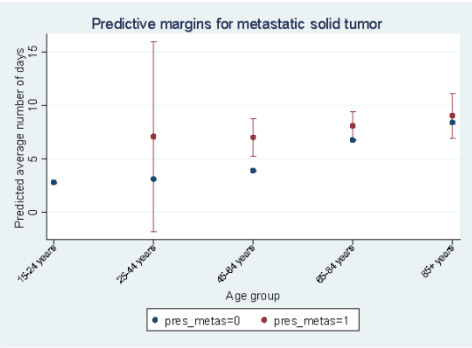

Predictive margins for hemiplegia/paraplegia
Predicted average number of days
5
6
7
8
9
Male
Female
Sex
pres_hemipara=0
pres_hemipara=1

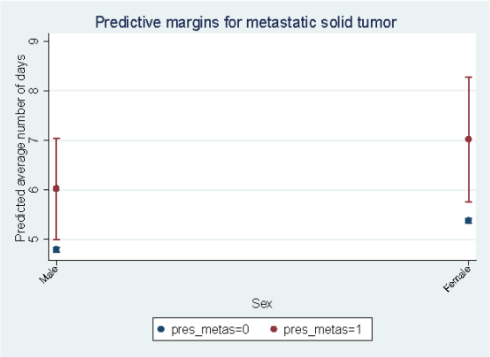

Predictive margins for hypertension uncomplicated
Predicted average number of days
2
4
6
8
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypertenuncomp=0
pres_hypertenuncomp=1

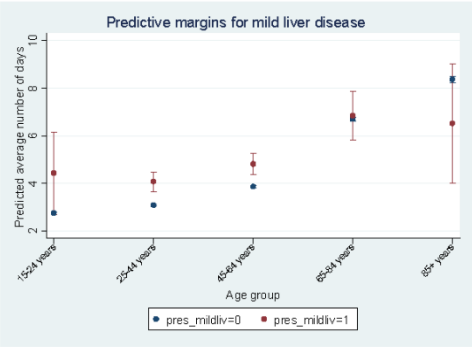

Predictive margins for hypertension uncomplicated
Predicted average number of days
4.5
5
5.5
6
6.5
Male
Female
Sex
pres_hypertenuncomp=0
pres_hypertenuncomp=1

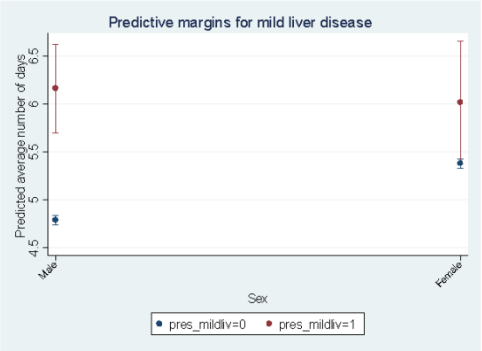

Predictive margins for hypothyroidism
Predicted average number of days
0
5
10
15
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypothy=0
pres_hypothy=1


Predictive margins for hypothyroidism
Predicted average number of days
4
6
8
10
12
Male
Female
Sex
pres_hypothy=0
pres_hypothy=1

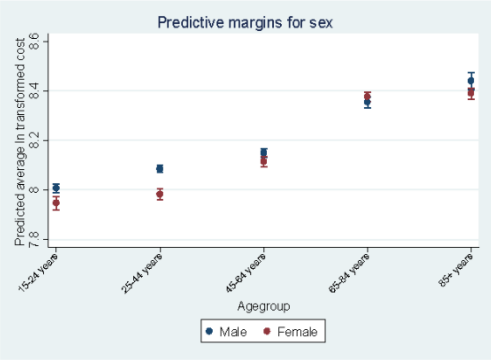


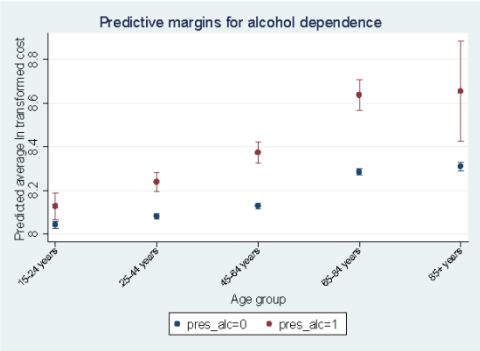


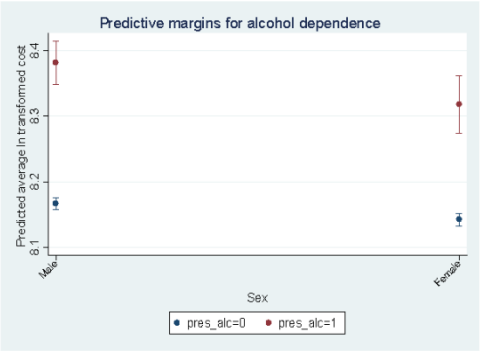


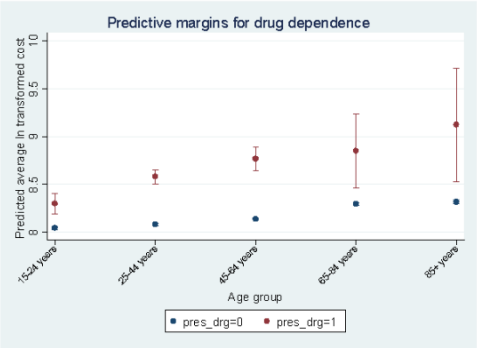


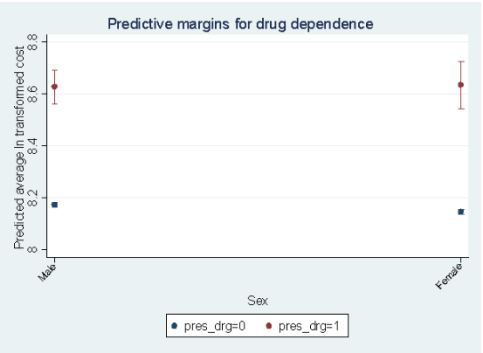
Hospital treatment cost

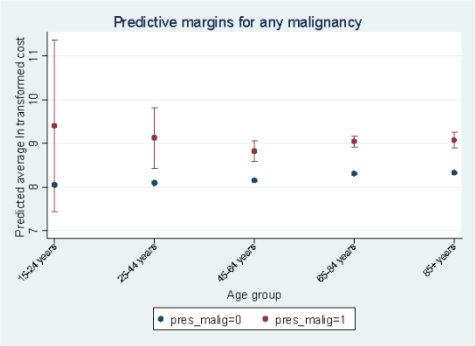


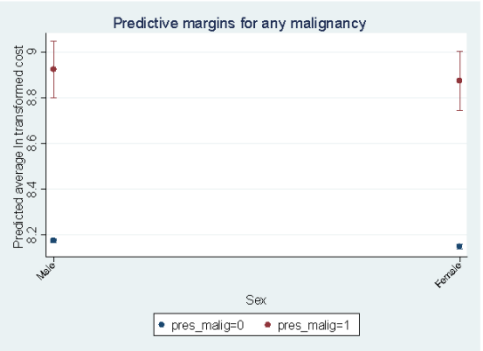

Predictive margins for alcohol dependence
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_alc=0
pres_alc=1

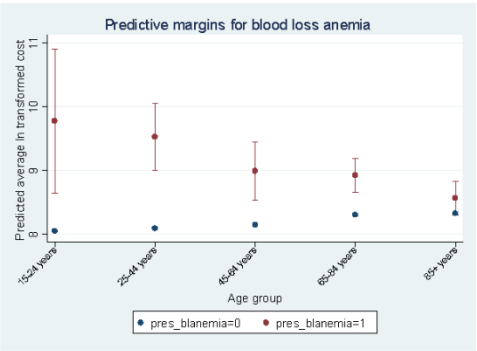

Predictive margins for alcohol dependence
Predicted average ln transformed cost
8.1
8.2
8.3
8.4
Male
Female
Sex
pres_alc=0
pres_alc=1

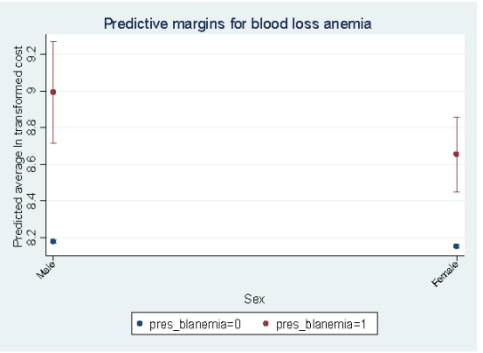

Predictive margins for drug dependence
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_drg=0
pres_drg=1

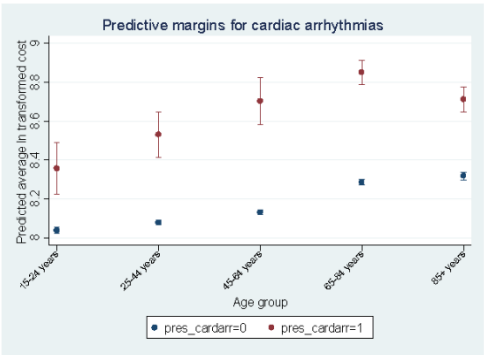

Predictive margins for drug dependence
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_drg=0
pres_drg=1

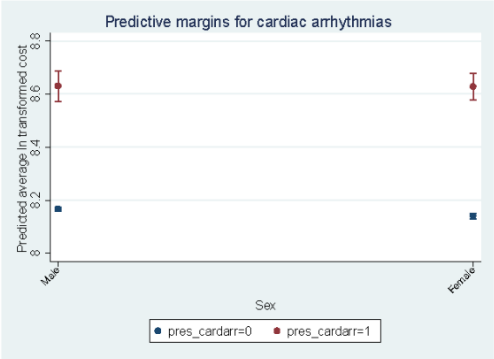

Predictive margins for any malignancy
Predicted average ln transformed cost
7
8
9
10
11
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_malig=0
pres_malig=1

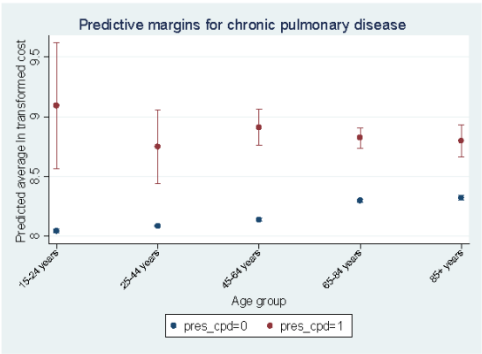

Predictive margins for any malignancy
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
Male
Female
Sex
pres_malig=0
pres_malig=1

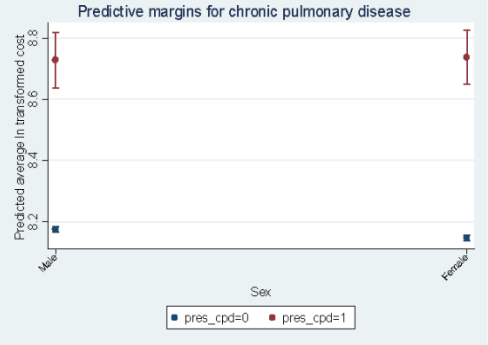

Predictive margins for blood loss anemia
Predicted average ln transformed cost
8
9
10
11
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_blanemia=0
pres_blanemia=1

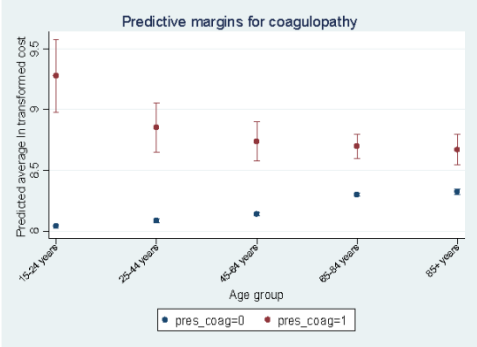

Predictive margins for blood loss anemia
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_blanemia=0
pres_blanemia=1

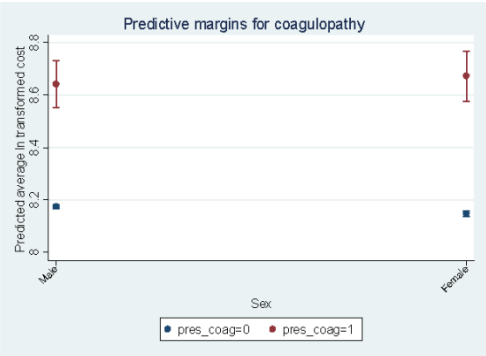

Predictive margins for cardiac arrhythmias
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cardarr=0
pres_cardarr=1

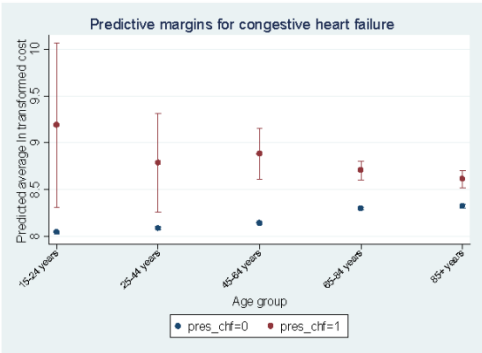

Predictive margins for cardiac arrhythmias
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_cardarr=0
pres_cardarr=1

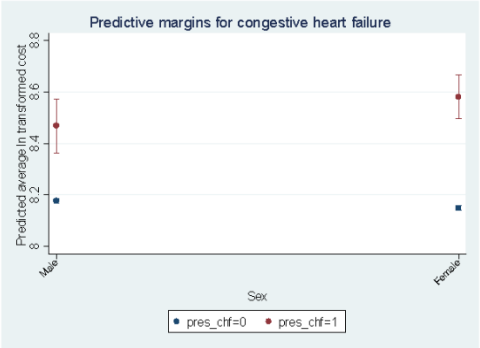

Predictive margins for chronic pulmonary disease
Predicted average ln transformed cost
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

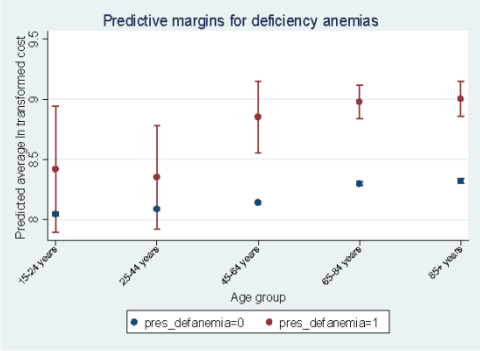

Predictive margins for chronic pulmonary disease
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_cpd=0
pres_cpd=1

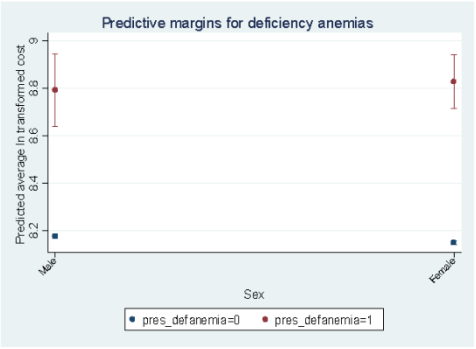

Predictive margins for coagulopathy
Predicted average ln transformed cost
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

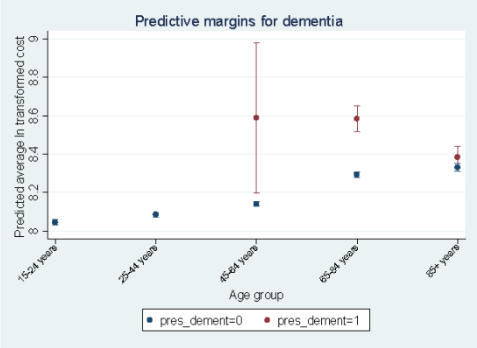

Predictive margins for coagulopathy
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_coag=0
pres_coag=1

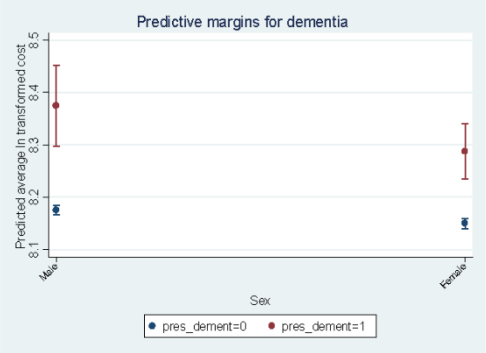

Predictive margins for congestive heart failure
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

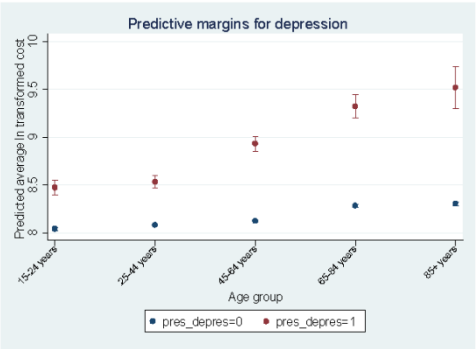

Predictive margins for congestive heart failure
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_chf=0
pres_chf=1

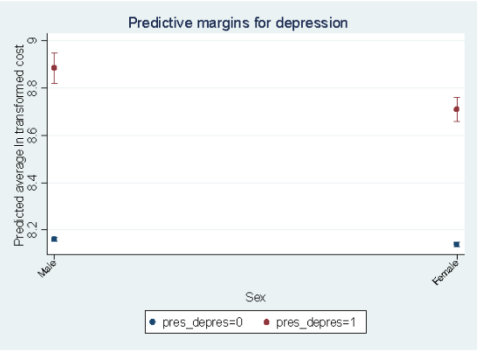

Predictive margins for deficiency anemias
Predicted average ln transformed cost
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_defanemia=0
pres_defanemia=1

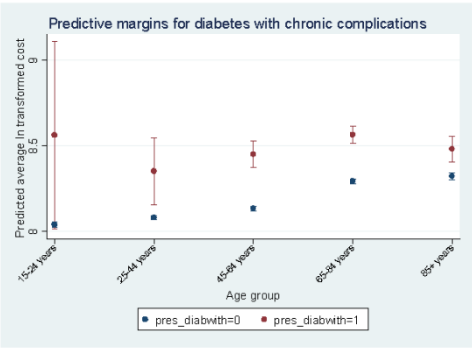

Predictive margins for deficiency anemias
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
Male
Female
Sex
pres_defanemia=0
pres_defanemia=1

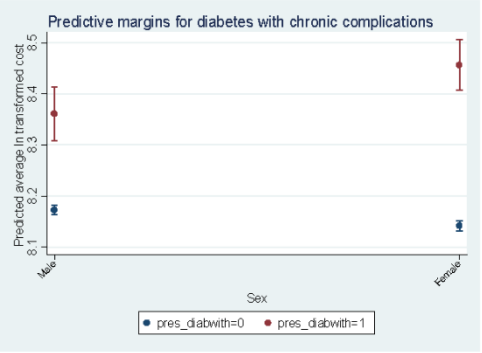

Predictive margins for dementia
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1

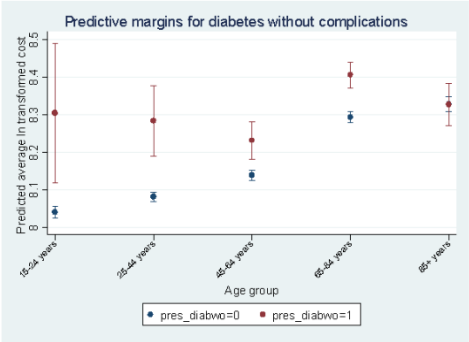

Predictive margins for dementia
Predicted average ln transformed cost
8.1
8.2
8.3
8.4
8.5
Male
Female
Sex
pres_dement=0
pres_dement=1

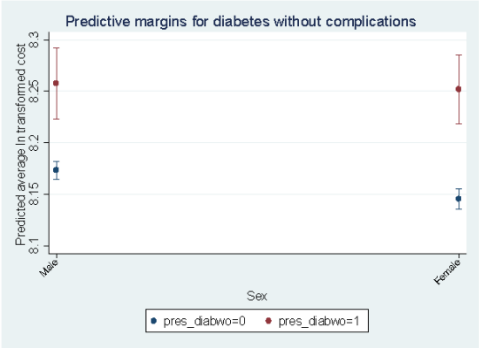

Predictive margins for depression
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_depres=0
pres_depres=1

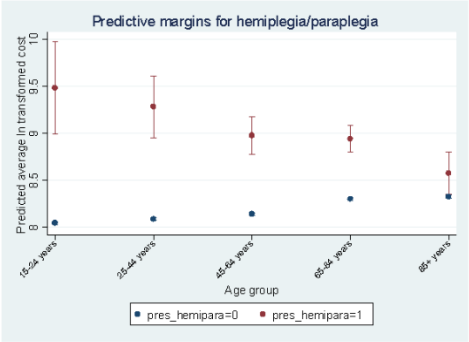

Predictive margins for depression
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
Male
Female
Sex
pres_depres=0
pres_depres=1

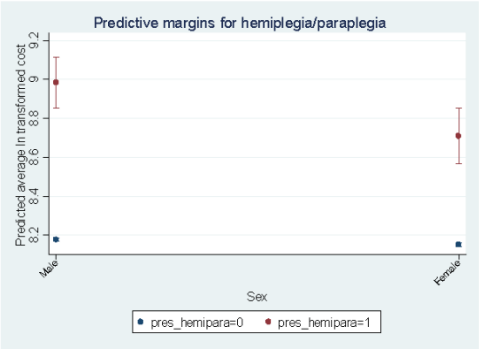

Predictive margins for diabetes with chronic complications
Predicted average ln transformed cost
8
8.5
9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

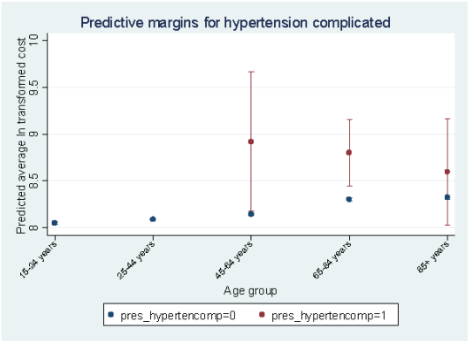

Predictive margins for diabetes with chronic complications
Predicted average ln transformed cost
8.1
8.2
8.3
8.4
8.5
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

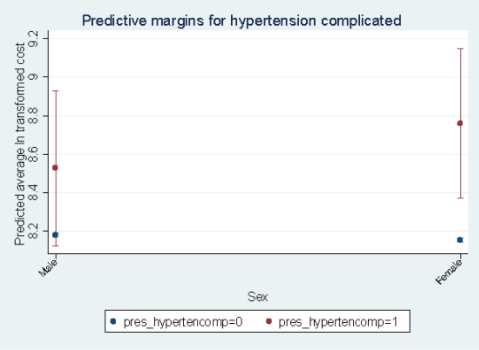

Predictive margins for diabetes without complications
Predicted average ln transformed cost
8
8.1
8.2
8.3
8.4
8.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

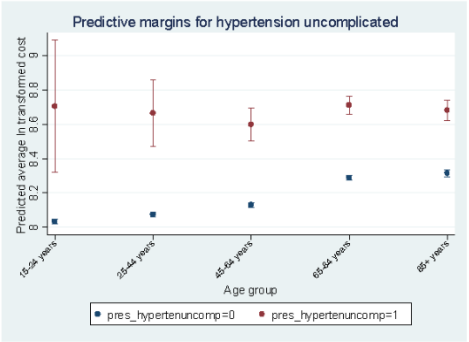

Predictive margins for diabetes without complications
Predicted average ln transformed cost
8.1
8.15
8.2
8.25
8.3
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

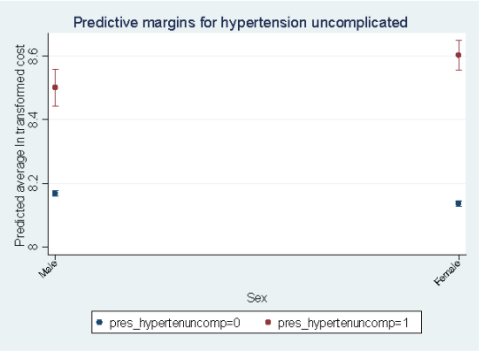

Predictive margins for hemiplegia/paraplegia
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hemipara=0
pres_hemipara=1

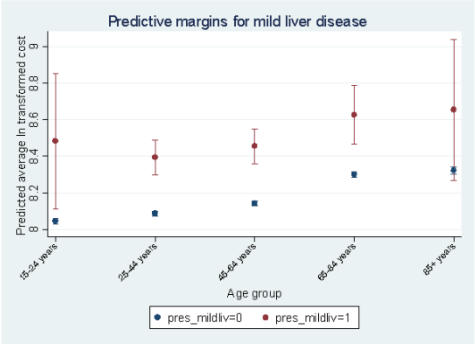

Predictive margins for hemiplegia/paraplegia
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_hemipara=0
pres_hemipara=1

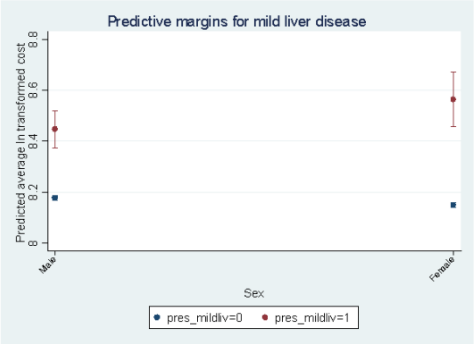

Predictive margins for hypertension complicated
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypertencomp=0
pres_hypertencomp=1

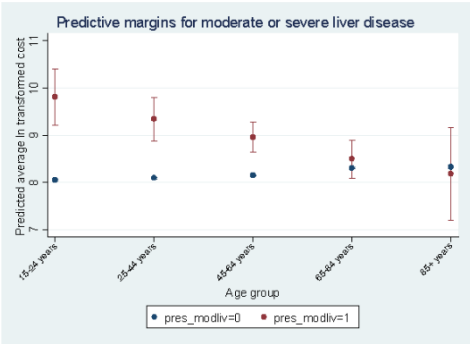

Predictive margins for hypertension complicated
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_hypertencomp=0
pres_hypertencomp=1

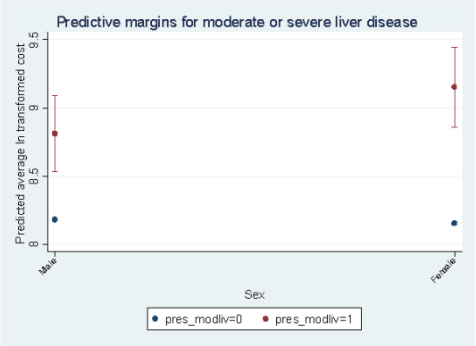

Predictive margins for hypertension uncomplicated
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypertenuncomp=0
pres_hypertenuncomp=1

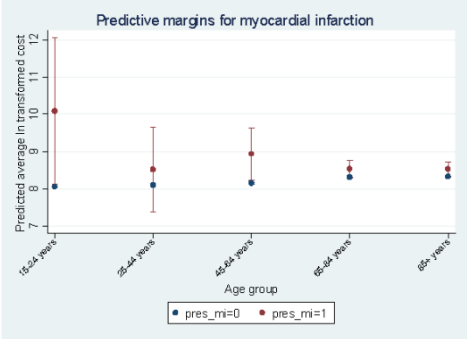

Predictive margins for hypertension uncomplicated
Predicted average ln transformed cost
8
8.2
8.4
8.6
Male
Female
Sex
pres_hypertenuncomp=0
pres_hypertenuncomp=1

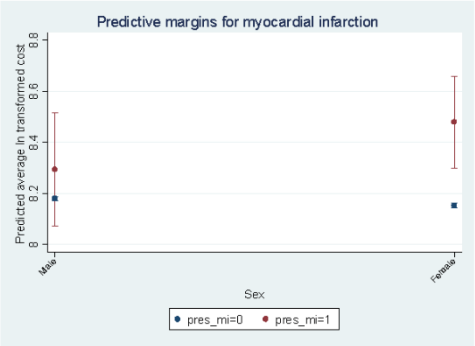

Predictive margins for mild liver disease
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
9
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1

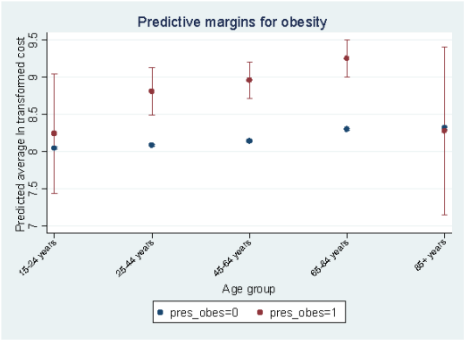

Predictive margins for mild liver disease
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

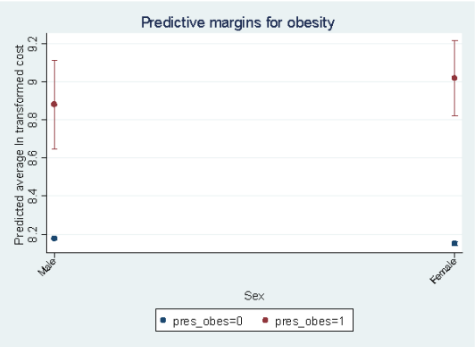

Predictive margins for moderate or severe liver disease
Predicted average ln transformed cost
7
8
9
10
11
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_modliv=0
pres_modliv=1

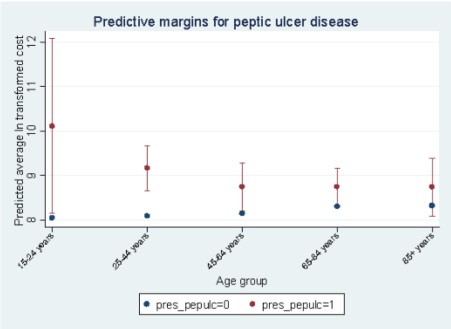

Predictive margins for moderate or severe liver disease
Predicted average ln transformed cost
8
8.5
9
9.5
Male
Female
Sex
pres_modliv=0
pres_modliv=1

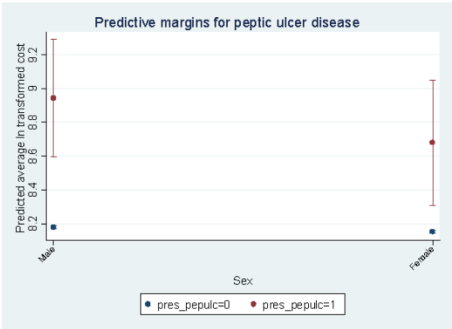

Predictive margins for myocardial infarction
Predicted average ln transformed cost
7
8
9
10
11
12
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mi=0
pres_mi=1

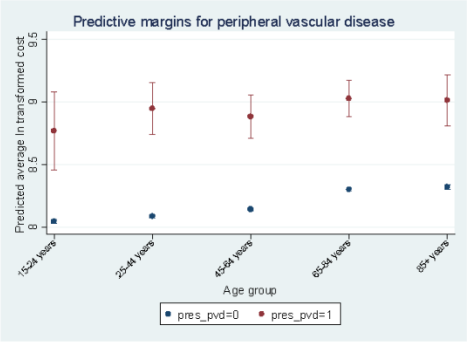

Predictive margins for myocardial infarction
Predicted average ln transformed cost
8
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_mi=0
pres_mi=1

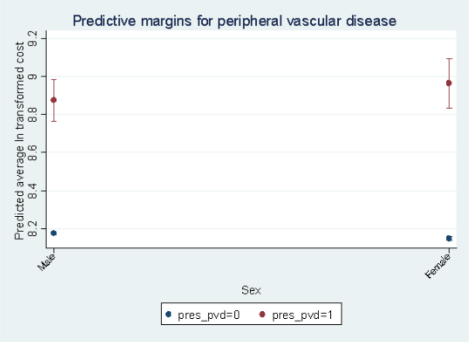

Predictive margins for obesity
Predicted average ln transformed cost
7
7.5
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_obes=0
pres_obes=1

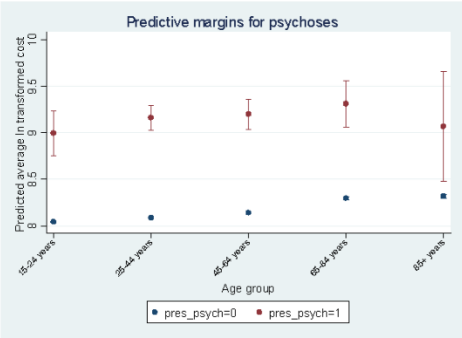

Predictive margins for obesity
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_obes=0
pres_obes=1

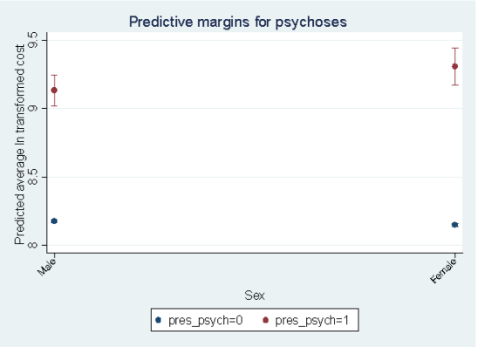

Predictive margins for peptic ulcer disease
Predicted average ln transformed cost
8
9
10
11
12
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pepulc=0
pres_pepulc=1

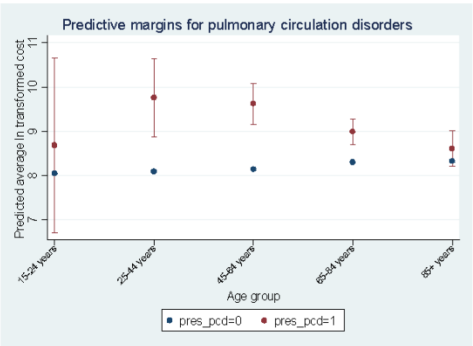

Predictive margins for peptic ulcer disease
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_pepulc=0
pres_pepulc=1

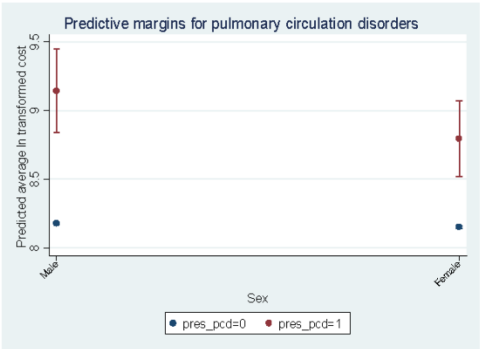

Predictive margins for peripheral vascular disease
Predicted average ln transformed cost
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pvd=0
pres_pvd=1

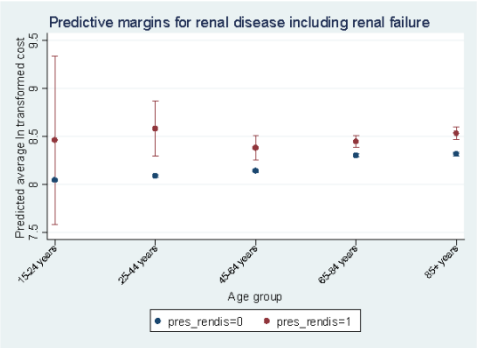

Predictive margins for peripheral vascular disease
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_pvd=0
pres_pvd=1

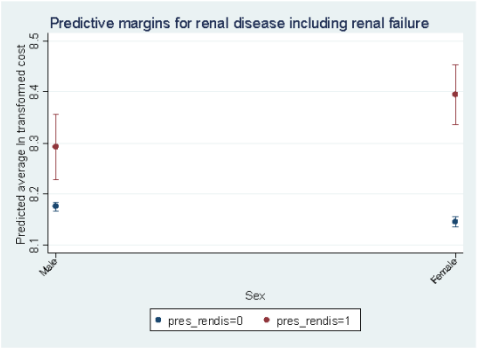

Predictive margins for psychoses
Predicted average ln transformed cost
8
8.5
9
9.5
10
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_psych=0
pres_psych=1

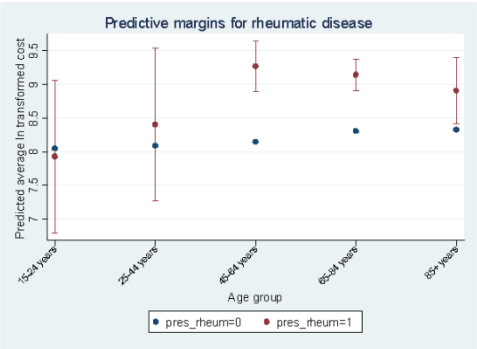

Predictive margins for psychoses
Predicted average ln transformed cost
8
8.5
9
9.5
Male
Female
Sex
pres_psych=0
pres_psych=1

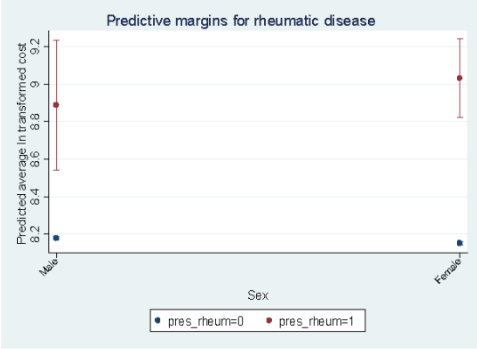

Predictive margins for pulmonary circulation disorders
Predicted average ln transformed cost
7
8
9
10
11
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_pcd=0
pres_pcd=1

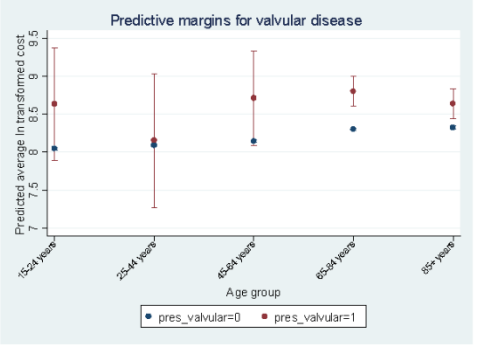

Predictive margins for pulmonary circulation disorders
Predicted average ln transformed cost
8
8.5
9
9.5
Male
Female
Sex
pres_pcd=0
pres_pcd=1

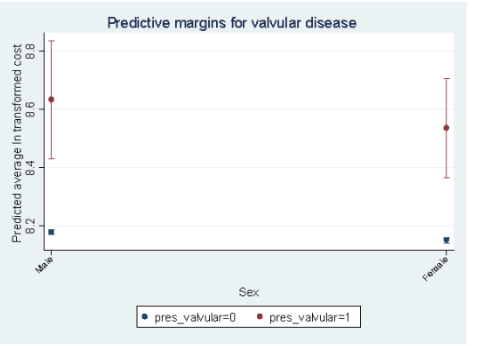

Predictive margins for renal disease including renal failure
Predicted average ln transformed cost
7.5
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rendis=0
pres_rendis=1


Predictive margins for renal disease including renal failure
Predicted average ln transformed cost
8.1
8.2
8.3
8.4
8.5
Male
Female
Sex
pres_rendis=0
pres_rendis=1

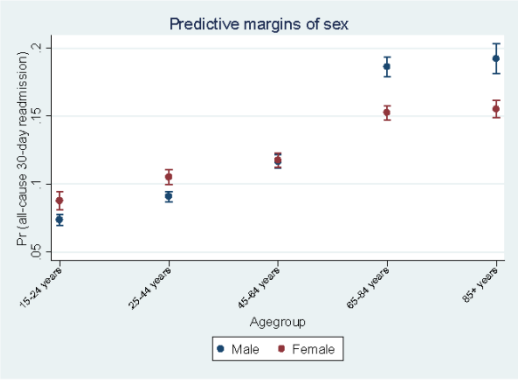

Predictive margins for rheumatic disease
Predicted average ln transformed cost
7
7.5
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rheum=0
pres_rheum=1

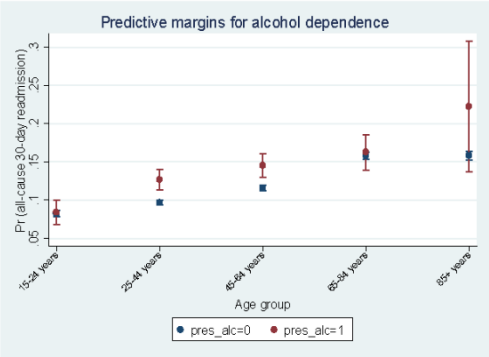

Predictive margins for rheumatic disease
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
9
9.2
Male
Female
Sex
pres_rheum=0
pres_rheum=1

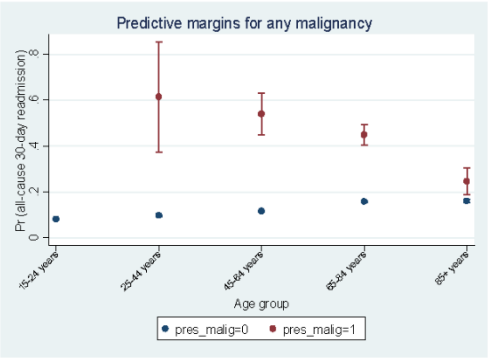

Predictive margins for valvular disease
Predicted average ln transformed cost
7
7.5
8
8.5
9
9.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_valvular=0
pres_valvular=1

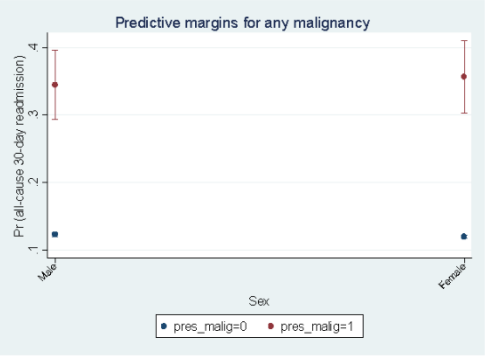

Predictive margins for valvular disease
Predicted average ln transformed cost
8.2
8.4
8.6
8.8
Male
Female
Sex
pres_valvular=0
pres_valvular=1

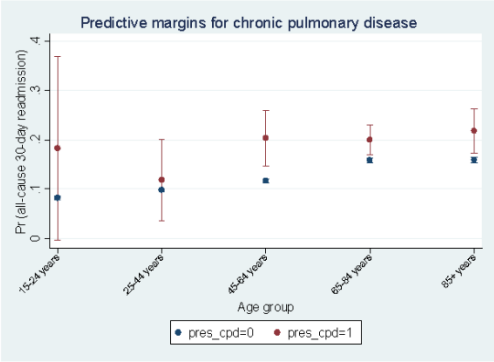
All-cause 30-day readmissions

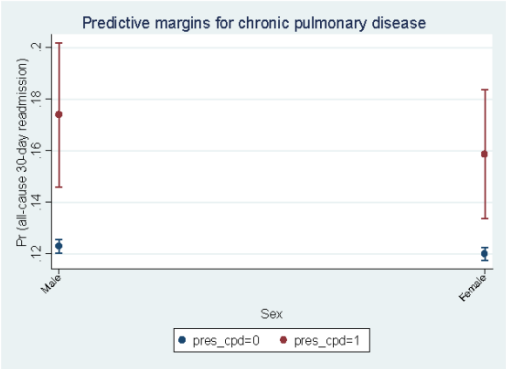


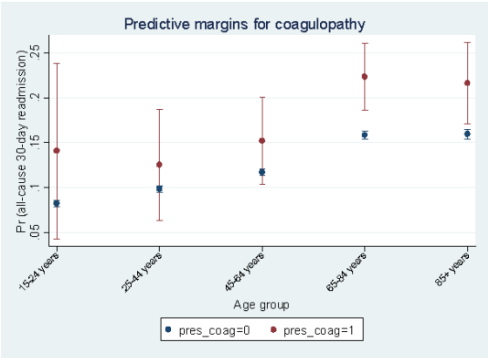


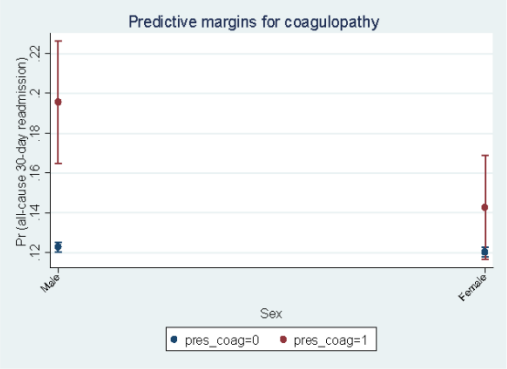


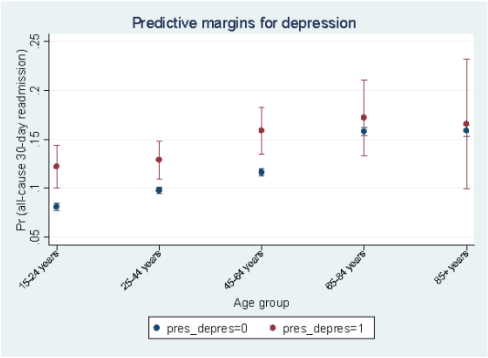


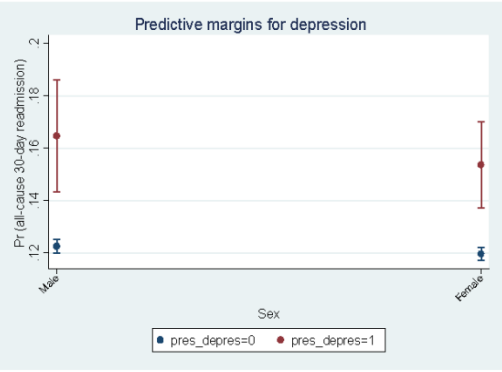

Predictive margins for chronic pulmonary disease
Pr (all-cause 30-day readmission)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

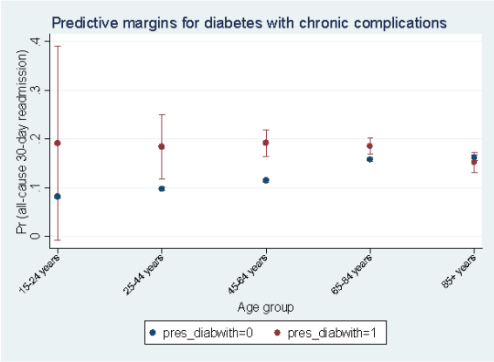

Predictive margins for chronic pulmonary disease
Pr (all-cause 30-day readmission)
.12
.14
.16
.18
.2
Male
Female
Sex
pres_cpd=0
pres_cpd=1

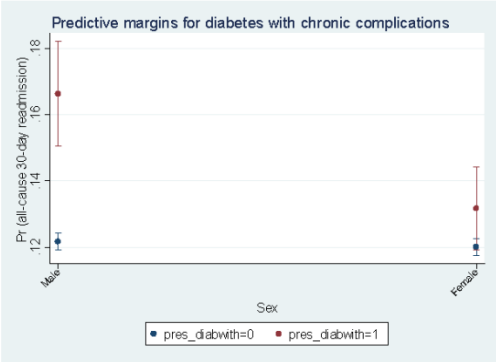

Predictive margins for coagulopathy
Pr (all-cause 30-day readmission)
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

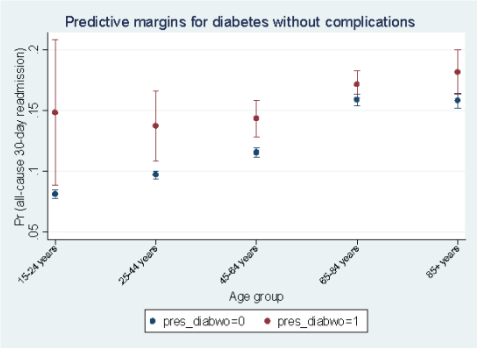

Predictive margins for coagulopathy
Pr (all-cause 30-day readmission)
.12
.14
.16
.18
.2
.22
Male
Female
Sex
pres_coag=0
pres_coag=1

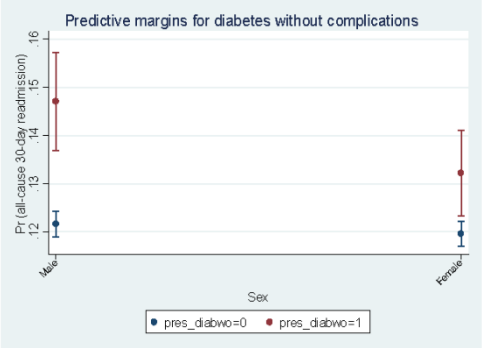

Predictive margins for depression
Pr (all-cause 30-day readmission)
.05
.1
.15
.2
.25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_depres=0
pres_depres=1

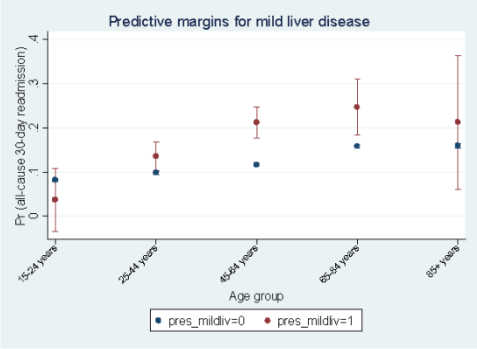

Predictive margins for depression
Pr (all-cause 30-day readmission)
.12
.14
.16
.18
.2
Male
Female
Sex
pres_depres=0
pres_depres=1

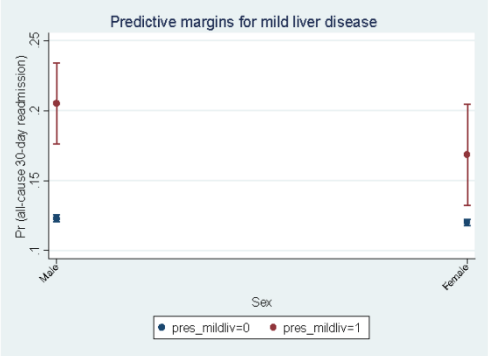

Predictive margins for diabetes with chronic complications
Pr (all-cause 30-day readmission)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

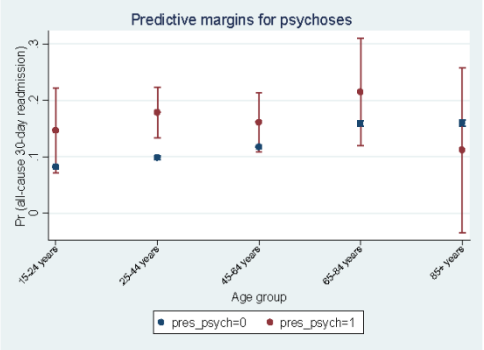

Predictive margins for diabetes with chronic complications
Pr (all-cause 30-day readmission)
.12
.14
.16
.18
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

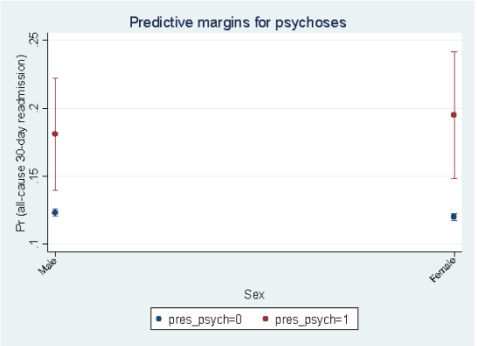

Predictive margins for diabetes without complications
Pr (all-cause 30-day readmission)
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

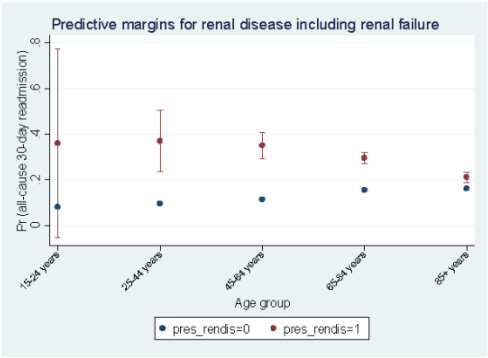

Predictive margins for diabetes without complications
Pr (all-cause 30-day readmission)
.12
.13
.14
.15
.16
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

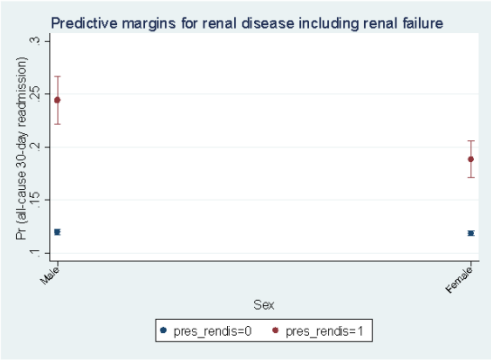

Predictive margins for mild liver disease
Pr (all-cause 30-day readmission)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1


Predictive margins for mild liver disease
Pr (all-cause 30-day readmission)
.1
.15
.2
.25
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1

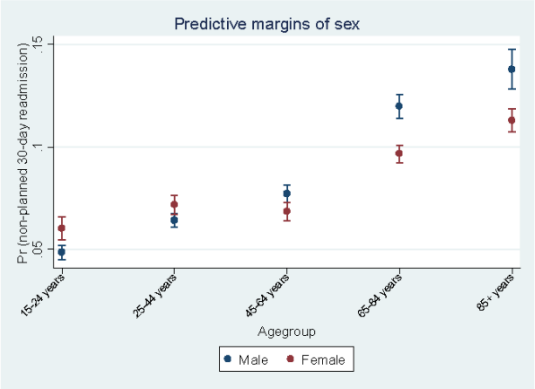

Predictive margins for psychoses
Pr (all-cause 30-day readmission)
0
.1
.2
.3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_psych=0
pres_psych=1

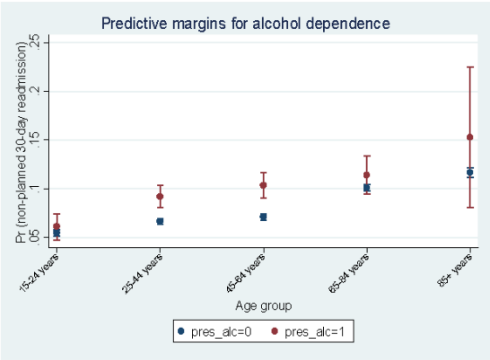

Predictive margins for psychoses
Pr (all-cause 30-day readmission)
.1
.15
.2
.25
Male
Female
Sex
pres_psych=0
pres_psych=1

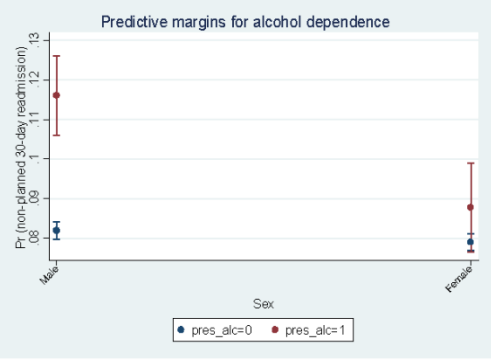

Predictive margins for renal disease including renal failure
Pr (all-cause 30-day readmission)
0
.2
.4
.6
.8
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rendis=0
pres_rendis=1

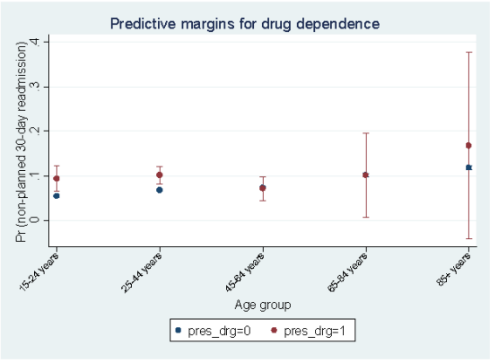

Predictive margins for renal disease including renal failure
Pr (all-cause 30-day readmission)
.1
.15
.2
.25
.3
Male
Female
Sex
pres_rendis=0
pres_rendis=1

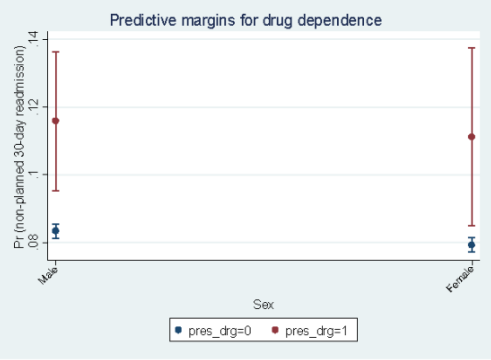
Non-planned 30-day readmissions

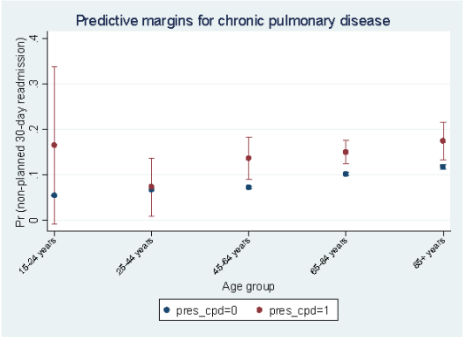


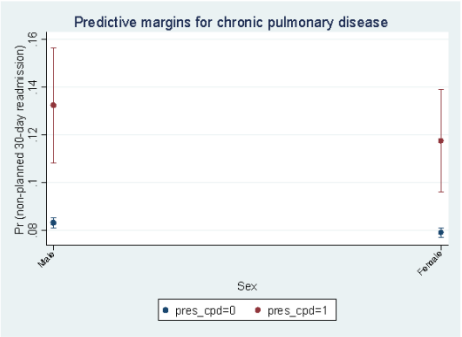


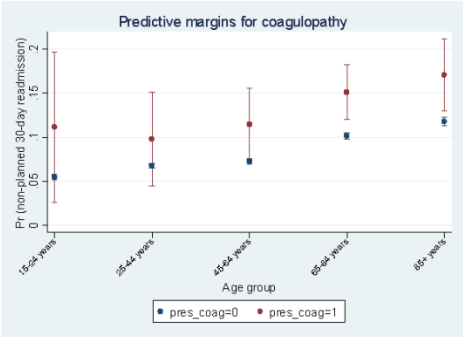


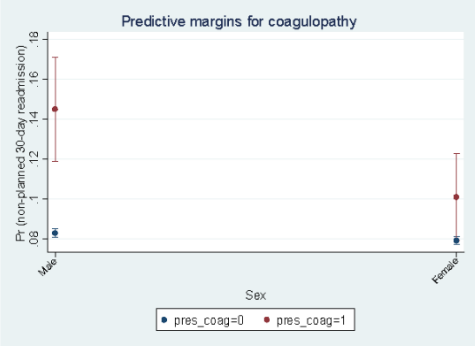


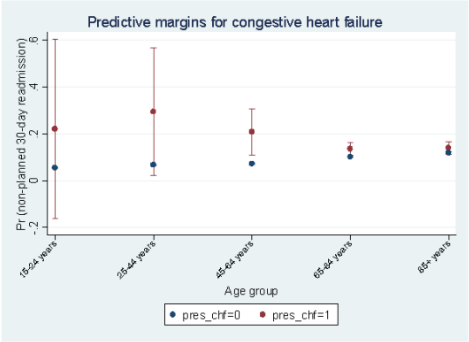


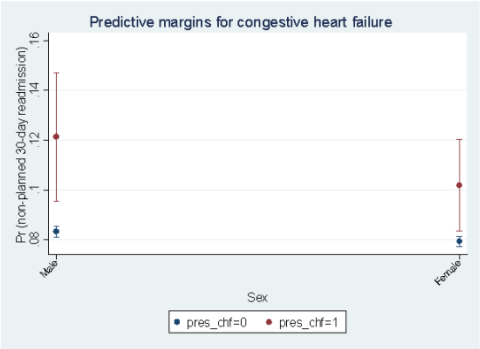

Predictive margins for chronic pulmonary disease
Pr (non-planned 30-day readmission)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

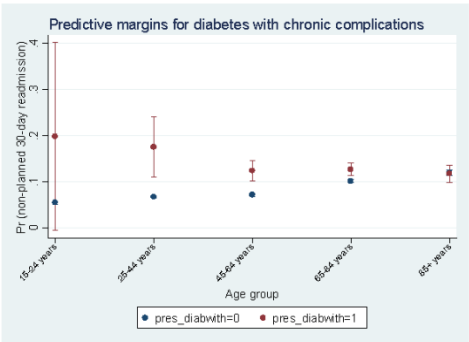

Predictive margins for chronic pulmonary disease
Pr (non-planned 30-day readmission)
.08
.1
.12
.14
.16
Male
Female
Sex
pres_cpd=0
pres_cpd=1

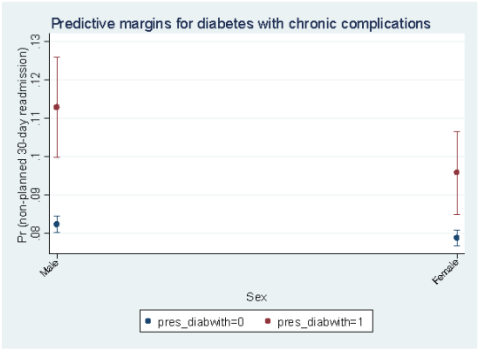

Predictive margins for coagulopathy
Pr (non-planned 30-day readmission)
0
.05
.1
.15
.2
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

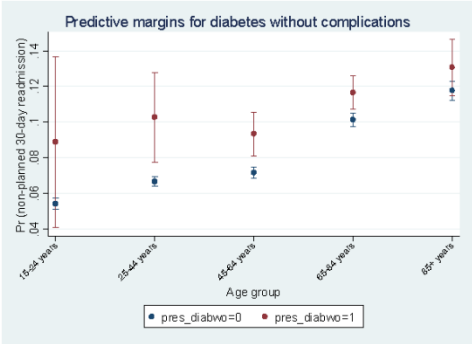

Predictive margins for coagulopathy
Pr (non-planned 30-day readmission)
.08
.1
.12
.14
.16
.18
Male
Female
Sex
pres_coag=0
pres_coag=1

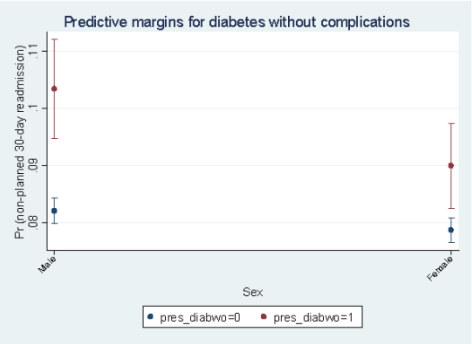

Predictive margins for congestive heart failure
Pr (non-planned 30-day readmission)
-.2
0
.2
.4
.6
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

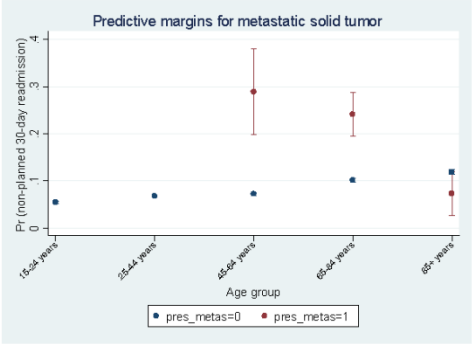

Predictive margins for congestive heart failure
Pr (non-planned 30-day readmission)
.08
.1
.12
.14
.16
Male
Female
Sex
pres_chf=0
pres_chf=1

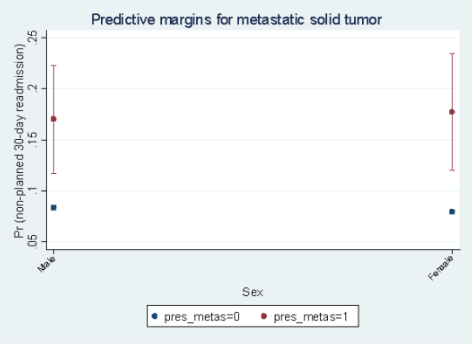

Predictive margins for diabetes with chronic complications
Pr (non-planned 30-day readmission)
0
.1
.2
.3
.4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwith=0
pres_diabwith=1

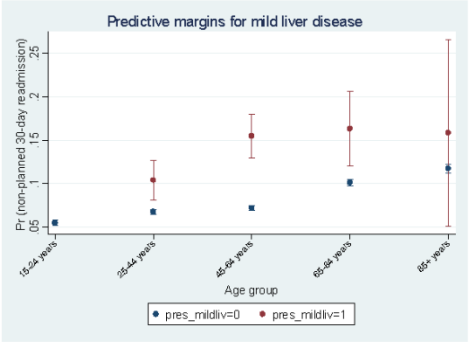

Predictive margins for diabetes with chronic complications
Pr (non-planned 30-day readmission)
.08
.09
.1
.11
.12
.13
Male
Female
Sex
pres_diabwith=0
pres_diabwith=1

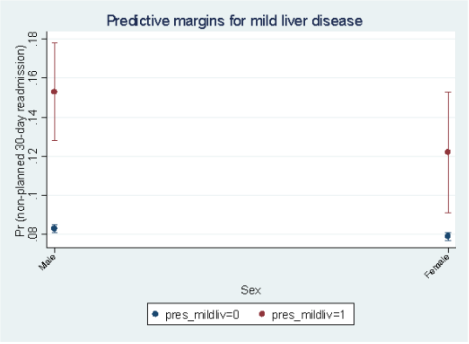

Predictive margins for diabetes without complications
Pr (non-planned 30-day readmission)
.04 .06 .08 .1 .12 .14
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_diabwo=0
pres_diabwo=1

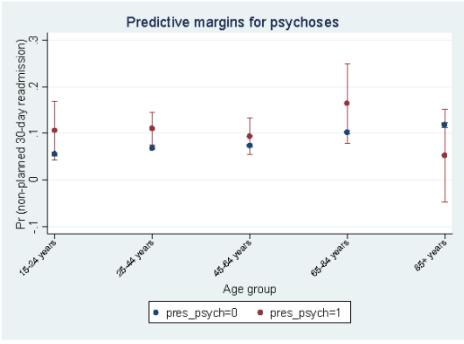

Predictive margins for diabetes without complications
Pr (non-planned 30-day readmission)
.08 .09 .1 .11
Male
Female
Sex
pres_diabwo=0
pres_diabwo=1

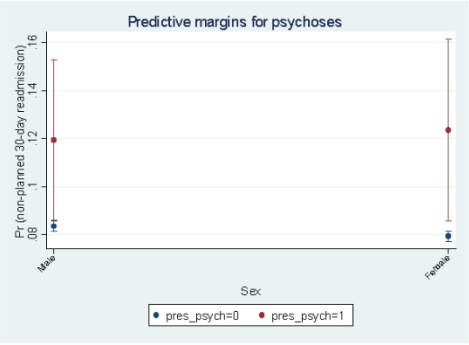

Predictive margins for metastatic solid tumor
Pr (non-planned 30-day readmission)
0 .1 .2 .3 .4
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_metas=0
pres_metas=1

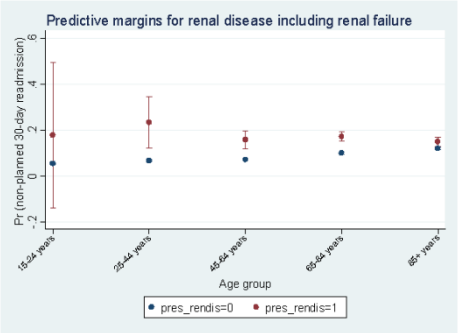

Predictive margins for metastatic solid tumor
Pr (non-planned 30-day readmission)
.05 .1 .15 .2 .25
Male
Female
Sex
pres_metas=0
pres_metas=1

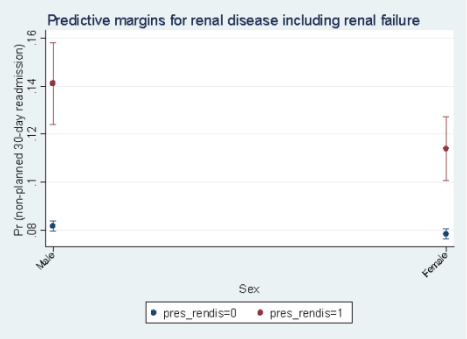

Predictive margins for mild liver disease
Pr (non-planned 30-day readmission)
.05 .1 .15 .2 .25
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_mildliv=0
pres_mildliv=1


Predictive margins for mild liver disease
Pr (non-planned 30-day readmission)
.08 .1 .12 .14 .16 .18
Male
Female
Sex
pres_mildliv=0
pres_mildliv=1


Predictive margins for psychoses
Pr (non-planned 30-day readmission)
-.1 0 .1 .2 .3
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_psych=0
pres_psych=1


Predictive margins for psychoses
Pr (non-planned 30-day readmission)
.08 .1 .12 .14 .16
Male
Female
Sex
pres_psych=0
pres_psych=1


Predictive margins for renal disease including renal failure
Pr (non-planned 30-day readmission)
-.2
0
.2
.4
.6
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_rendis=0
pres_rendis=1


Predictive margins for renal disease including renal failure
Pr (non-planned 30-day readmission)
.08
.1
.12
.14
.16
Male
Female
Sex
pres_rendis=0
pres_rendis=1

1 Internal validation

All model fit results in Appendix table A4 and FNs in Table 5.

1.1 Overnight stay

All indices added with the baselines had good discrimination (AUC>= 0.7) for all subgroups, except for penetrating trauma (AUCs<0.7). The predictive power in terms of AUCs were the same for the AICI-os, AICI-b and ECM across all subgroups. The best discrimination was seen for the older adults (>65 years) and adults with intracranial injuries. The ability to discriminate was significantly poor for the CCI among older adults, males, females, non-severe injury patients and hip fractures (CIs of the CCI did not overlap with the CIs of the AICIs or ECM). The FNs for the AICI-os were significantly lower than the for the CCI when validated among children, older adults, males, females, patients with non-severe injuries, hip fractures and blunt trauma. The AICI-os also reported significantly lower FNs than the ECM among children. In all, the new indices validated better than the CCI among *all* and the ECM among *certain* subgroups.

1.2 LOS (for patients with at least one overnight stay)

All subgroups' validations returned adjusted R^2s lesser than the original (full dataset) for all indices, except for the male subgroup. For children, the R^2s were half the original but fared better than the older adults whose R^2 was around 20-30% of the original. Validation was poorest among those with hip fractures, while non-severe injury and intracranial injury patient groups returned lesser than but close to the original R^2s. Validations returned better R^2s for blunt over penetrating trauma and for males than females. The new indices and the ECM had better model fit and higher predictive power in all subgroups compared to the CCI. ECM validates better than the new indices at the cost of an extra three to seven conditions.

1.3 Cost

Using the adjusted R^2 as a comparison measure, all indices validated a little poorly among children, males, non-severe injury and penetrating injury patients compared to the whole dataset. They validated better among older adults, females, intracranial and blunt injury patients compared with the entire dataset. The new indices outperformed the CCI on average by about three percentage points in all subgroups except among children, whilst among hip fracture patients the AICI-cost outperformed the ECM as well.

1.4 All-cause 30-day readmission

All subgroups presented similar predictive ability in terms of the AUC statistics for all indices with all CIs overlapping. There was no significant difference between the FN rates for all indices across sub groups except that they were significantly lower for the ECM among children, older adults, females and blunt trauma patients. In all, the model nor the new or existing indices provide enough power to predict this outcome.

1.5 Non-planned 30-day readmission

Similar to all-cause readmissions, all subgroups presented similar predictive ability in terms of the AUC statistics for all indices with all CIs overlapping. Significant differences for FN rates were only seen between the following; ECM lower than the AICI-npr and CCI among older adults, males, females, patients with hip fractures and blunt trauma while the ECM was higher than the AICI-npr and CCI for children. The AICI-npr also had a lower FN rate than the CCI for penetrating trauma. In this instance, though the ECM was better suited for certain subgroups, the overall power to predict was insufficient in this model.

2 External validation

The NSW and WA validation cohorts presented similar patterns to the Victorian cohort in terms of demographics, injury characteristics and comorbidity (Table 1 and Appendix Table A1). The only differences were; (1) the overall number of patients in groups varied (which is in relation to the size of the state populations), (2) WA cohort had a smaller proportion (around one-fifth) of older adults admitted compared to the other two states (around one-third) and (3) the median length of stay for those with at least one comorbidity in the WA cohort was half of that in the other two states (2 (IQR 1-10)).

All model fit results in Appendix Table A6 and FNs in Table 5.

2.1 Overnight stay

The predictive abilities in terms of the AUC statistics were good for all indices (AUC>0.7) and significantly higher in NSW than WA, but both lower than Victoria. They were similar for the AICI-os and ECM (CIs were overlapping), but significantly lower for the CCI. There were no significant differences between the FN rates of the AICI-os, ECM and CCI in both the NSW and WA cohorts. All indices validated well with the new indices having an advantage over the CCI in terms of predictive power and over the ECM in terms of a lesser number of comorbidities.

2.2 LOS (for patients with at least one overnight stay)

All indices validated best in WA, followed by Victoria and NSW in terms of highest adjusted R^2s. Highest R^2s were for the ECM, followed by AICI-los and CCI.

2.3 All-cause and non-planned 30-day readmission

As in the case of Victoria, the AUC statistics for modelling the new and existing indices with readmissions reveal poor predictive powers in NSW and WA as well (AUC<0.7). Apart from having low AUCs, the CIs overlap between the AICI-acr, CCI and ECM implying they are not significantly different in terms of predictive powers. Model fit was best in the ECM followed by AICI-acr and CCI (using the AIC). All-cause readmissions validated best in WA data, followed by Victoria and NSW and non-planned readmissions validated best in WA data, followed by NSW and Victoria. Overall, the model needs improvement regardless of the comorbidity index given that the AUCs lie below 0.7.

Appendix A4 – Using the Australian Injury Comorbidity Indices

The Australian Injury Comorbidity Indices for burden and readmission are recommended for use in epidemiological research where LOS, cost, all-cause and non-planned readmissions are outcomes of interest.

Option I

Model the presence of each comorbidity as a dummy variable with 1 for disease presence and 0 for absence along with other main effects. The index for LOS was derived to aid outcome prediction for up to 30 days stay while the readmissions indices were for readmissions within 30 days of discharge. Note that the conditions included in the indices vary with the outcome, unless the more parsimonious index is used.

Option II

Another option is to use a score derived by adding the presence/absence of conditions for each index as shown in Table A8.1. The total score derived is used as the comorbidity indicator. Table A8.2 shows the scores for the Victorian study population based on percentiles.

In prediction modelling, this option results in similar predictive power for all outcomes but higher false negative rates for overnight stay compared to option I.

Option II would be more useful in a clinical setting where patient classification is required, in the absence of retrospective data. The use of this score would need significant validations before it can be reliably used.

Table A8.1: Index calculation for a general injury patient cohort

Comorbidity	AICI-os	AICI-los	AICI-cost	AICI-b	AICI-acr	AICI-npr	AICI-r
HIV/AIDS							
Alcohol dependence	1	1	1	1	1	1	1
Drug dependence	1	1	1	1		1	
Any malignancy	1	1	1	1	1		
Blood loss anaemia	1	1	1	1			
Cardiac arrhythmia	1	1	1	1			
Cerebrovascular disease		1					
Chronic pulmonary disease	1	1	1	1	1	1	1
Coagulopathy	1	1	1	1	1	1	1
Congestive heart failure	1	1	1	1		1	
Deficiency anaemias	1	1	1	1			
Dementia	1		1				
Depression	1	1	1	1	1		
Diabetes with chronic complications	1	1	1	1	1	1	1
Diabetes without complications	1	1	1	1	1	1	1
Hemiplegia/paraplegia	1	1	1	1			
Hypertension complicated			1				
Hypertension uncomplicated	1	1	1	1			
Hypothyroidism	1	1	1	1			
Metastatic solid tumor		1				1	
Mild liver disease	1	1	1	1	1	1	1

Moderate or severe liver disease	1	1	1	1			
Myocardial infarction			1				
Obesity	1	1	1	1			
Peptic ulcer disease		1	1				
Peripheral vascular disease	1	1	1	1			
Psychoses	1	1	1	1	1	1	1
Pulmonary circulation disorders		1	1				
Renal disease including renal failure	1	1	1	1	1	1	1
Rheumatic disease including some other connective tissue disorders	1	1	1	1			
Valvular disease	1	1	1	1			
Maximum total comorbidity score	24	27	28	23	10	11	8

Table A8.2: Minimum and maximum scores for injury comorbidity indices at selected percentiles for the Victorian cohorts (age >15 years)

Percentile	AICI-os	AICI-los	AICI-cost	AICI-b	AICI-acr	AICI-npr	AICI-r
25th							
50th							
75th							
0-75th		0-0					
76th		1-1					
0-76th	0-0		0-0				
77th	1-1		1-1				
0-77th				0-0			
78th				1-1			
0-82nd					0-0		
83rd					1-1		
0-83rd						0-0	
84th						1-1	
0-84th							0-0
85th							1-1
93rd	2-2	2-2	2-2				
94th				2-2			
97th					2-2	2-2	
98th	3-3	3-3	3-3	3-3			2-2
99th							
100th	4-8	4-9	4-9	4-8	3-6	3-5	3-5

6 Injury comorbidity indices for in-hospital complications

This chapter includes a manuscript submitted (in February 2020) to *the BMJ*

(Editor awaiting reviewer reply)

titled

"The Australian Injury Comorbidity Indices (AICIs) to predict in-hospital complications: a population-based data linkage study".

(attached at the end of the chapter)

As discussed at the start of the previous chapter and in the conclusions drawn at the end of it, it is clear that the associations between comorbidities and outcomes are quite varied depending on the outcome. Therefore, for the outcomes of interest in this section of the thesis: *in-hospital complications*, specifically assessing the associations between these and comorbidities is warranted.

During hospital stay, patients may develop hospital-acquired complications (e.g., intra and post procedural complications, adverse drug events, infections etc.) while there is also a possibility to be admitted to the ICU or placed on the MV. Pre-existing comorbidity could trigger or aggravate such events. Due to the current lack of outcome- and population-specific comorbidity indices, existing indices such as the CCI and ECM, which were not derived for in-hospital complications, are widely applied for assessing these, including among specific injury populations. The aim of this chapter was to derive indices to specifically capture the effect of comorbidity on ICU and MV use and hospital-acquired complications (identified using the CHADx) for injury patients. As in the previous two chapters, the new indices were then be compared with

existing indices, and both the new and existing indices were validated in population subgroups and interstate data from NSW and WA.

The research questions that will be answered in this chapter are similar to the previous chapter, but based on in-hospital complications. They are:

1. Based on the analysis of Victorian data:
    a. How can comorbidity best be quantified?
    b. Does an updated comorbidity index perform significantly better than the CCI, updated CCI by Quan et al. and the ECM in predicting injury outcomes?
    c. Do the indices' performance (predictive ability) vary among subgroups of the population?
2. Do the indices developed on Victorian data effectively capture the effect of comorbidity on injury outcomes in other Australian states?

6.1 Summary

Analysis showed the association between comorbidities and in-hospital complications varied, depending on the outcome. Three new binary indices for ICU hours, MV hours and number of CHADx complications (AICI-icu, AICI-mv, AICI-comp) were derived. Three other binary indices were also derived for specific CHADx complications: gastrointestinal, cardiovascular and metabolic disorders. Once again, a binary representation of comorbidities was found to be similar in terms of predictive abilities to a weighted comorbidity index and was also better than an indicator of the presence of at least one or the count of comorbidities. This answers questions 1a: how can comorbidity best be quantified?

The AICIs performed equally well or slightly poorer than the ECM in predicting the outcomes but outperformed the CCI; not withholding the fact that the AICIs uses far fewer comorbidities and only includes those with a significant association with the outcome. This answers questions 1b: do the new indices perform better than the CCI and ECM (in terms of complications) outcomes?

The validation of all new and existing indices in subgroups depended on the outcome and the subgroup. Their performances were either similar or, in some instances, the AICIs and ECM outperformed the CCI. This answers question 1c: do the indices' performance (predictive ability) vary among subgroups of the population?

To answer question 2; not all indices (new or existing) were equally robust across states; further work is required to understand the underlying dynamics within interstate populations, data collections and the outcomes themselves.

A parsimonious comorbidity index for all in-hospital complications could not be derived as the associations between comorbidities and outcomes were far too varied.

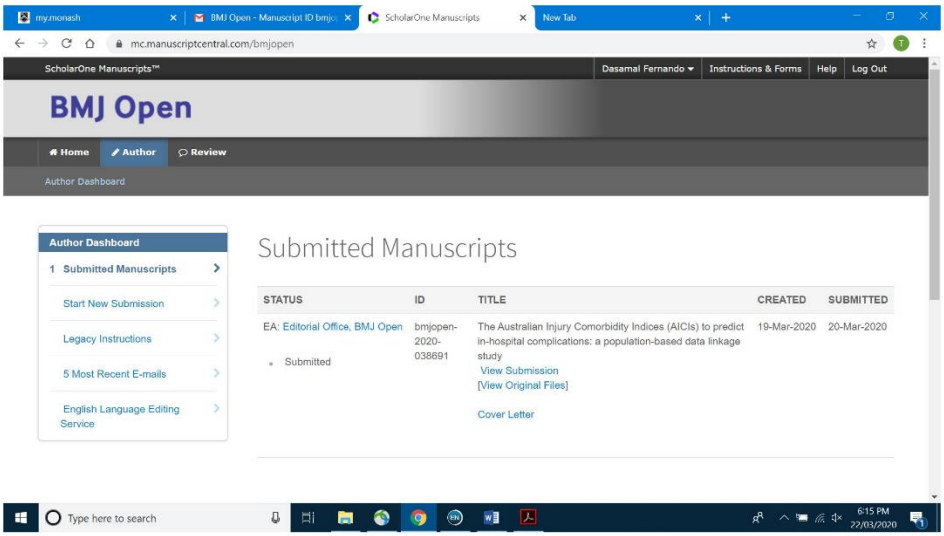
All in-hospital complications-related indices were different to the mortality-, burden- and readmission-related indices derived in the previous chapters.

6.2 Implications

In a clinical context, the new in-hospital-complications-related indices are potentially more useful than the existing indices due to the relevance to the specific outcomes. The parsimonious AICIs are more practical for use in clinical settings and in epidemiological research, because they use fewer comorbidities than the CCI (in some instances) and ECM in all instances. They are therefore less resource intensive in settings where data is not already collected but has to be *newly collected* on comorbidities.

The AICI-comp, which captures the association between comorbidity and the number of complications, may not be of practical relevance in a clinical context; the actual effect on the 17 individual CHADx complication groups will differ. This implies a requirement for complication-specific (i.e., based on the type of CHADx complication) comorbidity indices which would be more useful in clinical settings.

This study is one of the first to examine the effect of 31 comorbidities on hospital acquired complications for injury patients. Since these are 'hospital-acquired' complications, the associations are likely to be similar for general patients. It would be worthwhile to derive the complication-related indices for general patients and then validate these on injury patients as part of a future study, or on the contrary, validate the injury indices on general medical patients.


my.monash
BMJ Open - Manuscript ID bmjo
ScholarOne Manuscripts
New Tab
mc.manuscriptcentral.com/bmjopen
ScholarOne Manuscripts™
Dasamal Fernando
Instructions & Forms
Help
Log Out
BMJ Open
Home
Author
Review
Author Dashboard
Author Dashboard
1 Submitted Manuscripts
Start New Submission
Legacy Instructions
5 Most Recent E-mails
English Language Editing Service
Submitted Manuscripts
STATUS
ID
TITLE
CREATED
SUBMITTED
EA: Editorial Office, BMJ Open
Submitted
bmjopen-2020-038691
The Australian Injury Comorbidity Indices (AICIs) to predict in-hospital complications: a population-based data linkage study
View Submission
[View Original Files]
Cover Letter
19-Mar-2020
20-Mar-2020
Type here to search
6:15 PM
22/03/2020

BMJ Open

The Australian Injury Comorbidity Indices (AICIs) to predict in-hospital complications: a population-based data linkage study

Journal:	*BMJ Open*
Manuscript ID	Draft
Article Type:	Original research
Date Submitted by the Author:	n/a
Complete List of Authors:	Fernando, Dasamal; Monash University Accident Research Centre, Victorian Injury Surveillance Unit Berecki-Gisolf, Janneke; Monash University, Monash University Accident Research Centre Newstead, Stuart; Monash University, Monash University Accident Research Centre Ansari, Zahid; Victoria Department of Health and Human Services, Victorian Agency for Health Information
Keywords:	TRAUMA MANAGEMENT, EPIDEMIOLOGY, PUBLIC HEALTH

I, the Submitting Author has the right to grant and does grant on behalf of all authors of the Work (as defined in the below author licence), an exclusive licence and/or a non-exclusive licence for contributions from authors who are: i) UK Crown employees; ii) where BMJ has agreed a CC-BY licence shall apply, and/or iii) in accordance with the terms applicable for US Federal Government officers or employees acting as part of their official duties; on a worldwide, perpetual, irrevocable, royalty-free basis to BMJ Publishing Group Ltd ("BMJ") its licensees and where the relevant Journal is co-owned by BMJ to the co-owners of the Journal, to publish the Work in this journal and any other BMJ products and to exploit all rights, as set out in our licence.

The Submitting Author accepts and understands that any supply made under these terms is made by BMJ to the Submitting Author unless you are acting as an employee on behalf of your employer or a postgraduate student of an affiliated institution which is paying any applicable article publishing charge ("APC") for Open Access articles. Where the Submitting Author wishes to make the Work available on an Open Access basis (and intends to pay the relevant APC), the terms of reuse of such Open Access shall be governed by a Creative Commons licence – details of these licences and which Creative Commons licence will apply to this Work are set out in our licence referred to above.

Other than as permitted in any relevant BMJ Author's Self Archiving Policies, I confirm this Work has not been accepted for publication elsewhere, is not being considered for publication elsewhere and does not duplicate material already published. I confirm all authors consent to publication of this Work and authorise the granting of this licence.

The Australian Injury Comorbidity Indices (AICIs) to predict in-hospital complications: a population-based data linkage study

Tharanga Fernando (0000-0003-2423-3784), Janneke Berecki-Gisolf, Stuart Newstead, Zahid Ansari

Tharanga Fernando
PhD candidate
Monash University, Accident Research Centre, Clayton Campus,
21 Alliance Lane, Victoria 3800, Australia

Janneke Berecki-Gisolf
Associate Professor
Monash University, Accident Research Centre, Clayton Campus,
21 Alliance Lane, Victoria 3800, Australia

Stuart Newstead
Associate Professor
Monash University, Accident Research Centre, Clayton Campus,
21 Alliance Lane, Victoria 3800, Australia

Zahid Ansari
Associate Professor
Victorian Agency for Health Information,
50 Lonsdale Street, Melbourne, Victoria 3000, Australia

Correspondence to: T Fernando tara.fernando@monash.edu, Monash University, Accident Research Centre, Clayton Campus, 21 Alliance Lane, Victoria 3800, Australia

Abstract

Objective

Hospital-admitted patients are at risk of experiencing certain adverse outcomes during their hospital-stay. Patients may need to be admitted to the intensive care unit (ICU) or be placed on the mechanical ventilator (MV) while there is also a possibility for complications to develop. Pre-existing comorbidity could increase the risk of these outcomes. The Charlson Comorbidity Index (CCI) and the Elixhauser Comorbidity Measure (ECM), originally derived for mortality outcomes among general medical populations, are widely used for assessing these in-hospital complications even among specific injury populations. This study derived indices to specifically capture the effect of comorbidity on ICU and MV use as well as hospital-acquired complications for injury patients.

Methods

Retrospective data on injury hospital-admissions from July 2012 to June 2014 (161,334 patients) for the state of Victoria, Australia was analysed. Results from multivariable regression analysis were used to derive the Australian Injury Comorbidity Indices (AICIs) for ICU hours, MV hours and hospital-acquired complications. The AICIs, CCI and ECM were validated on data from Victoria and two other Australian states.

Results

Five comorbidities were significantly associated with ICU stay hours, two with MV hours and fifteen with hospital-acquired complications for hospitalised injury patients. Not all diseases listed in the CCI or ECM were found to be associated with these outcomes. The AICIs performed equally well in terms of predictive ability to the long-listed ECM and in most instances outperformed the CCI.

Conclusions

Associations between outcomes and comorbidities vary based on the type of outcome measure. The new comorbidity indices developed in this study provide a relevant, parsimonious and up-to-date method to capture the effect of comorbidity on in-hospital complications among admitted injury patients and is better suited for use in that context compared to the CCI and ECM.

Keywords: comorbidity, complication, index, injury, icu

Strengths and limitations of the study

- This study derived population- and outcome-specific comorbidity indices for injury which had been suggested in past research.
- The study also validated and compared some of the most widely used indices such as the Charlson Comorbidity Index and the Elixhauser Comorbidity Measure.
- The parsimonious Australian Injury Comorbidity Indices are more practical for use in clinical settings and in epidemiology.
- Limitations exist on the capture of comorbidity and comorbidity severity.
- Limitations also exist on the capture of hospital-acquired complications.

1. Introduction

Hospital-admitted patients can face certain adverse outcomes during their hospital stay. These include: admission to the intensive care unit (ICU), being placed on the mechanical ventilator (MV), development of complications and even mortality. ICU stay, MV use and complications result in increased burden (such as cost and length of stay (LOS)), and complications can also lead to mortality (1-3). Among hospital-admitted patients in Australia, the proportion of patients with at least one hospital-acquired complication was around 6.7% in 2010-11(4). Complications have been found to increase the risk of in-hospital death (7 times the risk) and to increase the length of stay (four times the mean LOS) while adding to the cost (4, 5) compared to those without complications.

A recent study found that patients admitted to hospital in relation to injury are more likely to develop complications than general admissions (Moor et al., 2015) (6). It found that hospital-acquired complications occurred in 13.9% of trauma patients, which was three times the proportion for general admissions. Other studies have reported various proportions of hospital-acquired complications among injury patients: 36.6% by Hoyts et al. (2003) (7), 10% by Holbrook et al. (2001) (8) and 13.3% by Fernando et al. (2019) (9). As has been reported for general patients, complications increase costs (3), LOS and mortality (2, 6) for injury patients.

Another contributor to adverse outcomes are pre-existing comorbidities. Ahmad et al. (2007) (10) showed that patients with diabetes mellitus were 1.8 times more likely to develop complications than those without, and they had a 50% greater ICU-LOS compared to those without complications. Among seriously injured older adults, pre-existing comorbidity increased complications by three-fold (11). Senn-Reeves et al. (2015) (12) also showed that comorbidity and injury characteristics were associated with injury-related complications.

The methods used to capture comorbidity in the past to assess their associations with outcomes are numerous. Most studies used a study-specific list of comorbidities (11, 13-15) or an abbreviated list from the National Trauma Data Bank (12). Others used the Charlson Comorbidity Index (CCI) (16-18), a weighted index derived to predict mortality outcomes. The CCI is rather dated since its initial derivation was in 1987 and significant medical advances that have taken place since then which might impact the relationship between comorbidities and outcomes. The Elixhauser Comorbidity Measure (ECM) is another measure used in epidemiological research (though less often than the CCI) for capturing comorbidity (19). The Mortality Risk Score for Trauma (MoRT) (20) derived for serious injury patients is the only injury-specific comorbidity index available at present. It was derived using a serious injury cohort so would be less versatile, given its specificity, in being generalised for all injury patients. The evidence also suggests that the ability of a comorbidity indicator to assess risk depends on the outcome being studied (19, 21, 22). Furthermore, the type of data available and prevalence of specific comorbidities in the population of interest is likely to be relevant when creating an indicator for comorbidity.

1.1 Study aims

The purpose of this study is: (1) to develop and validate new indices to assess the impact of comorbidity on outcomes of ICU stay, MV use and hospital-acquired complications using Australian administrative datasets and (2) to compare the performance of the new indices with the CCI and ECM.

2 Materials and Methods

2.1 Data sources

An observational study of existing hospital morbidity data was carried out. Retrospective Australian morbidity data for hospital-admitted injury patients were sourced from the Victorian Admitted Episodes Dataset (VAED), the Admitted Patient Data Collection (APDC) and the Hospital Morbidity Data Collection (HMDC), provided by the Centre for Victorian Data Linkage (CVDL) in Victoria, the Centre for Health Record Linkage (CHeReL) in New South Wales (NSW) and the Data Linkage Branch (DLB) in Western Australia (WA), respectively. All three datasets contain records of public and private hospital admissions with patient demographics and morbidity information. The morbidity data includes forty diagnosis codes for the VAED, fifty-one for the APDC and seventy-eight for the HMDC, containing disease, injury and external cause variables coded to the International Classification of Diseases Tenth Revision, Australian Modifications (ICD-10-AM) (23).

2.2 Data linkage

Records within each morbidity dataset were linked by the relevant data linkage units: (i) using deterministic data linkage for the VAED; (ii) probabilistic matching techniques for the APDC; and (iii) a multi-faceted probabilistic linkage that includes numerous automated and manual sub-processes for the HMDC. Using specific identifiers (unique to each data linkage unit), the records within each morbidity dataset were internally linked to allow for follow-up of hospital admissions subsequent to their index admission record over a period of two years. CVDL estimates the false positive match rate to be between 0.5% to 1%, and the false negative match rate to be between 1-2%. The two rates for the APDC are estimated to be around 0.5% (24). It is expected that the false negatives in the Western Australian Data Linkage System (WADLS) exceed the number of false positives; the derivation of specific estimates though are not attempted.

2.3 Case selection

Any record containing an ICD-10-AM diagnosis code in the range "S00" to "T75" or "T79" in the first appearing diagnosis field in the morbidity datasets was considered an injury case; similar to other national reporting (25). Cases were selected if they were index injuries (i.e., the first injury record for a patient during the study period) and limited to residents of the relevant state. Changes in care type within the same hospital or inward transfers from other hospitals were considered to be part of one episode if they appeared consecutively. Children below the age of 15 years were excluded when deriving indices as they differ to the rest of the cohort in terms of comorbidity prevalence. The Victorian cohort of adult patients consisted of 161,334 patients with an index injury admission between 01 July 2012 and 30 June 2014, the NSW cohort for the same period consisted of 233,521 patients and WA 84,877 patients.

2.3.1 Coding of outcomes, factors and comorbidities

2.3.1.1 Outcomes

Three outcomes related to in-hospital complications were coded and modelled for index derivation purposes: hours in the ICU, hours spent on the MV and the number of hospital-acquired complications. The hospital acquired complications were coded according to the classification of hospital acquired diagnoses (CHADx) (26). This is a common tool used in hospitals in a number of Australian states. The CHADx is grouped into 17 major classes expanding to 144 subclasses. Complications were determined for all index admissions and related admissions (i.e., complication codes recorded in transfers and statistical separations records, as well as readmissions with the same principal diagnosis code as the index principal diagnosis code or a principal readmission diagnosis code of T79, T80-T89 or T90-T98). Readmissions that took place more than six months after the index admission discharge were

excluded. All complications were coded using the CHADx hierarchy and summed to determine the total number of complications.

2.3.1.2 Explanatory variables (socio-demographics)

The baseline explanatory variables (factors) were age, gender, body-region of injury, injury type, injury severity, SEIFA (Socio Economic Indexes For Areas), country of birth, and geographic region (metropolitan or rural). Injury severity was calculated using the ICD-based Injury Severity Score (ICISS) (27). SEIFA was classified using the Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) expressed as state-deciles (28).

2.3.1.3 Explanatory variable (comorbidity)

The main predictor variable of interest was comorbidity. Comorbidities listed in the CCI (18) and ECM (19) were used in this study, based on the codes supplied in Quan et al. (2005) (29) and Sundararajan et al. (2005) (30). Thirty-one comorbidity groups were selected for this study. The ICD-10 codes corresponding with these comorbidity groups were searched for in the diagnosis fields of the morbidity datasets with the aid of the condition onset flags. The condition onset flag helps distinguish *comorbidities* from *primary conditions* and *complications*.

2.4 Statistical analysis

Associations between comorbidities and the three outcomes were assessed using multivariable regression analysis. The factor variables excluding comorbidity were entered in the baseline models. ICU and MV hours were modelled using linear regression with a log transformation while the number of complications was modelled using negative binomial regression. Adjusted and McFadden's R^2 were used to evaluate predictive powers of the models. The baseline models were then modified by adding comorbidity using various techniques: the presence of at least one of the thirty-one comorbidities, the count of comorbidities, a binary representation

of each comorbidity, the CCI (18), the updated CCI per Quan et al. (2011) (31), and ECM(19). The Akaike Information Criterion (AIC) (32) for model fit was used to compare the models.

The binary comorbidity indices were derived using a backward elimination process on the models with all thirty-one conditions fitted as binary variables. The resulting models excluded comorbidities that no longer improved model fit. This was ascertained using the AIC statistic (32); a difference < 10 between two AICs indicates that the model with the additional factors provides no further improvement to the model fit. Using the reduced binary model, weights were computed for each comorbid condition using the exponents of the parameters for comorbidities. A condition was dropped from the weighted index if the weight was less than 1.2 reflecting the lack of impact of this condition on the outcome, even if statistically significant. For weights above this, scoring was based on the range in which the weight fell; 1.2≤ weight <1.5 resulted in a score of 1; 1.5≤ weight <2.5=2 and so on. The sum of these weights created the summed weighted score, which became the weighted injury comorbidity index.

Five models were compared for best predictive ability. Baseline models included sociodemographic and injury factors; subsequently, comorbidity was introduced as follows: 1) binary representation, 2) weighted summed score, 3) CCI, 4) Updated CCI and 5) ECM (31). This process was carried out for each outcome.

Finally, the indices were internally validated in sub-groups (in terms of demographics, injury type and severity) and externally validated in NSW and WA data using the same baseline models and comorbidity indicators. The measures of validation were once again the R^2s as performed for the main analysis. Since the R^2s are proportions, tests for proportions were carried out to ascertain if the validation R^2s were significantly different to the R^2 in the main analysis. SAS software, Version 9.4 (33) and Stata 14.0 (StataCorp) (34) was used to analyse the data.

3 Results

3.1 Overview of study population

One-third of the Victorian cohort were older adults (>=65 years of age) and more than half were male (Table 1). Thirteen -percent were severely injured (per the ICISS) and nearly sixty-percent of the injuries were to the extremities, while the most common injury type was fracture (41%). Around 3% of patients required an ICU stay and 1.6% were on the mechanical ventilator. For adults, the mean ICU hours was 85.4 (95% CI 82.0 to 88.8) and MV hours was 75.2 (95% CI 70.3 to 80.2). Around 16% had at least one hospital-acquired complication. More than half of those requiring an ICU stay or MV use, and around 42% of those with complications, had at least one comorbidity.

Table 1: Characteristics of the Victorian, NSW and WA study populations

Adult patients with HIV/AIDS, cerebrovascular disease, coagulopathy, obesity and peripheral vascular disease spent five days (120 hours) or more on average in the ICU and on the MV (Table 2). The mean number of complications among adults ranged from 2.9 (95% CI 2.7 to 3.1) to 4.8 (95% CI 4.3 to 5.3) among the thirty-one comorbidities, with the highest mean being for patients with valvular disease (Table 2).

Table 2: Presence of comorbidity and the mean LOS in the ICU and MV, and the mean number of complications (Victoria, ages 15 years and over)

The proportion with complications was highest among patients with cardiac arrhythmias, diabetes without complications, uncomplicated hypertension and renal disease (Table 3). Gastrointestinal, cardiovascular, metabolic disorders and genitourinary complications were the most common types, each accounting for more than 10% of all complications (not shown in tables).

Table 3: Presence of comorbidity with CHADx complications (Victoria, ages 15 years and over)

3.2 Multivariable regression modelling

The baseline models (models *i*) differed for each outcome; details are presented in Table 4, with a step by step breakdown presented in Appendix table A1. The R^2 values for the baseline models for ICU and MV hours and complications were 10.4%, 14.5% and 2.9% respectively. Residual plots for ICU and MV hours and predicted vs observed plots for complications are presented in Appendix A1. Interaction effects between age and sex, age and comorbidities, and sex and comorbidities were also modelled, none of which improved the baseline models' predictive abilities significantly. Therefore, the interaction terms were excluded from further analysis although the margin plots for the interaction terms show some associations between certain comorbidities and the interaction between age and sex (Appendix A2).

The baseline models with the addition of various existing comorbidity indices are also presented in Table 4 and Appendix table A1. Among them are the newly derived binary (model *ii*) and weighted comorbidity indices (model *iii*) and existing indices (CCI (model *iv*), updated CCI (model *v*) and ECM (model *vi*)).

Table 4: Performance of selected comorbidity measures in assessing the association between comorbidity and selected outcome measures (Victoria)

3.2.1 ICU hours and MV hours

Assessing model fit using the AICs, the best was model *vi* (containing the ECM), followed by models *iii* (containing the new weighted injury comorbidity index) and *ii* (containing the Australian Injury Comorbidity Index for ICU hours (AICI-icu) with five comorbidities and the Australian Injury Comorbidity Index for MV hours (AICI-mv) with two comorbidities) (Table 4 and Appendix Table A1). The CCI (model *iv*) had a poorer fit.

3.2.2 Hospital-acquired complications

The best in terms of model fit was once again model *vi* (containing the ECM), followed by model *x* (containing all thirty-one comorbidities) and model *ii* (containing the Australian Injury Comorbidity Index for complications (AICI-comp) with fifteen comorbidities) (Table 4 and Appendix Table A1). The CCI (model *iv*) again had the poorest fit.

There was no gain in predictive power by using the lengthy ECM (see Table 4 and Appendix Table A1); the AICI-comp with fewer comorbidities was found to yield similar results and had at least a 0.5% advantage in terms of predictive power over the CCI.

3.2.3 Complication-type specific comorbidity indices

Three other comorbidity indices were also derived for the most prevalent complications in the study cohort. These were gastrointestinal, cardiovascular and metabolic disorders (model results and included comorbidities can be found in appendix tables A2 and A3). Fifteen comorbidities were found to be associated with the number of complications per the AICI-comp, but only 2-7 conditions were found to show association with the likelihood of specific complications (Appendix Table A2). For example, three comorbidities (alcohol dependence, moderate to severe liver disease and valvular disease) were only found to be associated with metabolic disorders and not the other two types of complications. Congestive heart failure was only associated with cardiovascular complications. Pre-existing cardiac arrythmias, chronic pulmonary disorders and uncomplicated hypertension were only associated with cardiovascular complications and metabolic disorders. This indicates that the associations between comorbidities and complications varies depending on the type of complication and needs due consideration in research and clinical settings.

Table 5: Risk adjusted beta coefficients, incident rate ratios, and suggested weights for ICU hours and complications among Victorian hospital-admitted injury patients

3.3 Comparison of conditions included in new and existing indices

The number of comorbidities associated with in-hospital complications for injury patients in this study were fewer compared to the comorbidities listed in the CCI and ECM. Many of the conditions listed in the CCI and/or ECM, such as HIV/AIDS, drug dependence, blood loss anaemia, malignancies, cerebrovascular disease, deficiency anaemias, diabetes without complications, hemiplegia/paraplegia, complicated hypertension, hypothyroidism, metastatic solid tumors, mild liver disease, myocardial infarction, peptic ulcer disease, pulmonary circulation disorders and rheumatic disease, were not associated with ICU hours, MV hours or hospital-acquired complications.

3.4 Internal validations

The AICI-icu and AICI-comp were validated in the following subgroups of the study cohort: age group 25-64 years, older adults (>=65 years), patients with severe injuries (defined using the ICISS and the worst injury method), and patients with intracranial injuries, hip fractures, blunt and penetrating trauma. The AICI-mv was not validated as the index only included two comorbidities.

3.4.1 ICU hours

The AICI-icu was validated on the 25-64 year age group as this group had a relatively high proportion of patients requiring the service (9). The R^2 for this age group and for patients with penetrating trauma was higher than for the full cohort (Appendix Table A4) while they were equal or less than the full cohort for the other subgroups. This indicates that the new indices work even better in the 25-64-year age group and patients with penetrating trauma, while it works poorly for hip fracture patients; the latter is expected as these patients are rarely treated in the ICU (only 7.4% of those with hip fractures over the age of 45 years required an ICU stay in Victoria (not shown in tables).

The performance in terms of the R^2 of the AICI-icu was similar to the ECM and CCI in most sub-groups except a few. In the 25-64-year age group, the ECM had the best predictive power, followed by the AICI-icu followed by the CCI, while among hip fracture patients >= 45 years of age, the ECM had the highest predictive power followed by the AICI-icu and CCI.

3.4.2 Complications

The AICI-comp was validated on the >=65-year age group and all other subgroups. For the >=65-year age group, the R^2 was less than the result for the full cohort; even less for severe injuries, intracranial injuries and hip fracture patients; equal for blunt trauma patients; and higher than the full cohort for penetrating trauma patients (Appendix Table A4). The R^2 of the AICI-comp was higher than that of the ECM and CCI for most of the subgroups except for the >=65-year age group, intracranial injuries and blunt trauma where it was equal to ECM or CCI. These results indicate that the AICI-comp, ECM nor the CCI is very suitable for serious injury, intracranial injuries or hip fracture patients.

3.5 External validations

Characteristics of the two validation cohorts (NSW and WA) can be found in Table1 and appendix tables A5 and A6. New and existing indices all fared similarly in the validation cohorts, i.e., if the new indices fared poorly, so did the existing indices and vice versa.

3.5.1 Comparing the performance of the AICI (in Victoria vs NSW and WA)

The AICI-icu's predictive power in the NSW data (7%) was poorer than in the Victorian data (12.1%) while it was much better in the WA data (23%) (Appendix Table A7). The AICI-comp's predictive power in the NSW data (2.3%) was poorer than in the Victorian data (3.6%) while it was equal in the WA data (3.7%). Overall, AICIs have validated well in WA but less so in NSW.

3.5.2 Comparing the performance of the AICIs against the CCI and ECM in NSW and WA

For ICU hours and complications, the ECM performed best in terms of the R^2, followed by the AICI-icu and CCI; but these differences were very small.

4 Discussion

The association between comorbidities and outcomes varied, depending on the comorbidity, the outcome and how the outcome was measured. Compared to the existing, most widely used index, the CCI, the new (and parsimonious) injury comorbidity indices were able to provide improved predictive power, while compared to the less often used ECM, the new indices performed equally or slightly worse. The new indices however only include comorbidities that are significantly associated with the outcomes, while the CCI and ECM includes comorbidities regardless of their association with the outcome.

4.1 Study strengths

This study demonstrated the variation in associations between comorbidity and outcomes, depending on the outcome measure, confirming suggestions from previous studies which recommended study- and outcome-specific comorbidity indices (35-39). These indices were derived using a population-based database; the indices are current and can be used for general injury patients.

Apart from developing new, outcome-specific comorbidity indices for injury patients, this study also validated and compared some of the most widely used indices such as the CCI, updated CCI and ECM, as well as other methods of measuring comorbidity, such as the presence of at least one comorbidity and the count of comorbidities. In comparing the comorbidities included in each index, it was observed that certain conditions that are listed in

the CCI and ECM, such as HIV/AIDS and peptic ulcer disease, were not associated with in-hospital complications in this group of patients. Though the CCI predicts mortality well, very few comorbidities were found to have an actual association with complications outcomes based on the AICIs. It is meaningless to associate comorbidities that have no relevance on the outcomes. The usefulness of indices like these depends on what is being done with them and why they are being employed. However, the CCI and ECM validated with very close predictive powers to the AICIs.

Furthermore, the study also showed that the application of specific weights to comorbidities did not significantly improve the predictive power of regression models above that of the binary representation of the conditions. Similar to the findings by Moor et al. (2008) (40), we found that the weights assigned to comorbidities in the CCI did not correspond to coefficients specific to this study, implying that each study cohort may require an empirical set of weights, if weights are to be used. The AICIs, which are a binary representation, may therefore be more suitable for use, weights are not required. This is in agreement with the conclusions drawn by Moor et al. (2008) (40) and Toson et al. (2015) (21) that binary representation of comorbidities was sufficient for representing the association between comorbidities and injury outcomes such as mortality and resource use.

Since hospital acquired complications may not be specific to injury patients, i.e., complications may be related to treatment and quality of care rather than the primary diagnosis, the AICI-comp could also be tested for use among general hospital-admitted patients.

The parsimonious AICIs are more practical for use in clinical settings and in epidemiology. They use a lesser number of comorbidities than the CCI (in some instances) and ECM in all instances. They are therefore less resource intensive in settings where data has to be collected on comorbidities.

4.2 Limitations

4.2.1 Significance testing

Significance testing in this study did little to exclude conditions from the models. Due to large sample sizes, most of the significance tests identified significant associations regardless of the effect size. Instead, to determine which factors were important in the models effect sizes were used in conjunction with the AIC statistic or pseudo R^2s to determine the impact of the condition on the overall predictive power of the model.

4.2.2 Capturing complications

Hospital acquired complications were captured using the CHADx, which is a coding system used by most Australian hospitals. The CHADx identifies certain diagnosis codes as hospital-acquired complications, with the aid of the main diagnosis codes and a secondary set of codes called the *condition onset flags*. These flags indicate whether the diagnosis was present at admission or occurred during the hospital stay. The number of complications identified in this study is not a perfect estimate of the total, due to: (1) limitations in using hospital administrative databases such as the VAED and (2) limitations of CHADx. Regarding (1): a previous study on the VAED (41) revealed that only 76.2% of admissions were correctly allocated a complication in the 'condition onset' flag, which means that this study could be failing to capture approximately one-quarter of the complications in the Victorian data. The proportion of diagnostic codes supplied with condition-onset flags indicative of a complication varied by state. We found the following proportions of records with a condition on-set flag indicating onset during admission: 18% in Victoria, 8.5% in NSW and 10% in WA. This may have contributed to the comorbidity indices poor validation results in NSW. Regarding (2), the drawback of the CHADx: although it aims to minimise double counting of complications, it has been shown to be less than perfect (42), due to the linear representation of conditions in the

diagnosis codes, leaving the possibility for some overestimation of CHADx conditions (42). Apart from this, some of the complications, although they occur during the hospital stay, may not be related to hospital treatment process, i.e., they could be related to the index condition with a lagged effect. However, in the absence of a more established and robust system for capturing complications (apart from using medical chart review which is not practical in large cohorts), the CHADx is considered sufficient for use with administrative data.

The use of administrative data for hospital-acquired complications surveillance has been criticised as not sufficient, due to the limits imposed by the number of diagnosis codes allowed in a database (43). However, with 40 or more diagnosis codes in each of the three datasets, this is not considered a limitation in this study.

Hospital-acquired complications could be affected by the hospital facilities, staffing and other variables: information that was not available for inclusion in this study. This information may have improved the baseline models and is recommended for future work to improve the predictive power of the models.

4.2.3 Capture of comorbidities

Hospital administrative data has also been criticised for not being able to fully capture all comorbidities for a patient. The main purpose of this type of data is to service administrative and financial planning of hospitals. In this context the coding of comorbidities that may not be actively treated or monitored could be ignored if they were unlikely to incur more resources. Further, the coding does not provide information on the severity of the recorded comorbidities. The reported comorbidities in the administrative data used in this study were only those present at hospital admission; furthermore, conditions were only recorded if they were actively monitored or treated. This situation will, however, improve in the future, as additional codes and requirements for coding comorbidity has been implemented in Australia (44).

Our study did not include lookback periods. However, the inclusion of these is only expected to increase comorbidity capture by about 10% (45). Lookback periods are impractical in clinical settings, but it may become more increasingly feasible in research settings with data linkage facilities.

The list of comorbidities used in this study was an amalgamation of the CCI and ECM lists, which results in the AICIs, CCI and ECM all performing within a similar predictive power bracket. We carried out a closer investigation of the prevalence rates of ICD-10 codes specific to our study cohort that were not included in the CCI and ECM lists. Codes with a prevalence rate of 1% or more were mainly symptoms such as nausea, vomiting etc and does not amount to chronic conditions and therefore excluded. Lowering the 1% cut-off to 0.5% and investigating those ICD-10 codes for inclusion into the AICIs is recommended for the future.

Model results can also be sometimes misleading if not interpreted with caution. For example, uncomplicated hypertension was associated with all outcomes, over the presence of complicated hypertension, which would not make sense. Uncomplicated hypertension may only get recorded if the patient was in hospital for a long time, and clinical staff become more vigilant in capturing 'everything'. This could result in an over-reporting of this condition, and its presence in the data may display a non-existent association in the model results. This problem can be averted if the severity of the comorbidities could be ascertained.

Given the varying performances of the indices in various subgroups of populations, these indices should be used with care and should not replace clinical judgement.

5 Conclusions

The association between in-hospital complications and comorbidities vary with the type of complication and comorbidity. This study derived complication-specific comorbidity indices that are up-to-date, relevant, parsimonious (therefore less resource intensive than existing

indices such as the CCI and ECM) and fairly robust. There is room to develop further-improved comorbidity indices for these and other complications, by improving the capture of information regarding both the comorbidities and the complications.

Ethics approval and consent to participate: The study was approved by the Monash University Human Research Ethics Committee (Project no: 1256), the New South Wales Population and Health Services Research Ethics Committee (REF: 2017/HRE0601) and the Department of Health WA Human Research Ethics Committee (RGS0000000613). Historical administrative data was used. The research is low risk in that there was no discomfort or risk of harm to the participants. Name, date of birth and other identifiers were removed from the dataset by the data custodians prior to release of the data to the researchers. Due to the magnitude of the dataset, it was impractical to obtain consent.

Availability of data and materials: The data that support the findings of this study are available from CVDL, CHeReL and WADLS but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. The authors are not in a position to release the data (in accordance with the agreement with CVDL, CHeReL and WADLS).

Dissemination declaration: We state that the dissemination of results related to the study to study participants and/or patient organisations is not possible/applicable.

Funding: This paper is part of a PhD thesis which is supported by the Victorian Injury Surveillance Unit (VISU) funded by the Victorian Government. The PhD student received the Australian Government Research Training Program scholarship stipend during the course of the project. This PhD project was initiated by VISU and therefore funds for purchasing data were supplied VISU. TF and JB are staff of VISU; however, the role of VISU was solely to be a source of data acquisition funding and supervision support. TF and JB had full access to all

of the data while all authors had access to statistical reports and tables in the study; TF and JB therefore take responsibility for the integrity of the data and the accuracy of the data analysis.

Transparency declaration: TF affirms that the manuscript is an honest, accurate, and transparent account of the study being reported; no important aspects of the study have been omitted.

Acknowledgements: The authors would like to thank the Centre for Victorian Data Linkage, the Centre Health Record Linkage in New South Wales and the Western Australian Data Linkage Branch and the custodians of data collections for providing linkage services and the data, and Prof. James Harrison at the National Injury Surveillance Unit for providing the survival risk ratios.

Contributorship statement: TF and JB conceived the presented idea, developed the theory, analysed and interpreted the data. SN verified the analytical methods while ZA facilitated data acquisition. JB, SN and ZA supervised TF in producing the findings of this work. All authors contributed to conceptualisation of the paper and read and approved the final manuscript. TF takes the responsibility for the overall content as guarantor. The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted. This research was done without patient involvement: only deidentified patient data was used. Patients were not invited to comment on the study design and were not consulted to develop patient relevant outcomes or interpret the results. Patients were not invited to contribute to the writing or editing of this document for readability or accuracy.

Mixed competing interests: All authors have completed the ICMJE uniform disclosure form at www.icmje.org/coi_disclosure.pdf and declare no support from any organisation for the submitted work. TF has received funding support from the Victorian Injury Surveillance Unit

(VISU) at Monash University to pay for two datasets and PhD supervision. No other relationships or activities that could appear to have influenced the submitted work.

6 References

1. De Jongh MAC, Bosma E, Verhofstad MHJ, et al. Prediction models for complications in trauma patients. Br J Surg 2011;98:790-796

2. Ingraham MA, Xiong RW, Hemmila LM, et al. The Attributable Mortality and Length of Stay of Trauma-Related Complications: A Matched Cohort Study. Ann Surg 2010;252:358-362

3. Hemmila MR, Jakubus JL, Maggio PM, et al. Real money: Complications and hospital costs in trauma patients. Surgery 2008;144:307-316

4. Trentino K, G Swain S, Burrows S, et al. Measuring the incidence of hospital-acquired complications and their effect on length of stay using CHADx. Med J Aust 2013;199:543-547

5. Ehsani JP, Jackson T, Duckett SJ. The incidence and cost of adverse events in Victorian hospitals 2003-04. Med J Aust 2006;184:551

6. Moore L, Lauzier F, Stelfox HT, et al. Validation of complications selected by consensus to evaluate the acute phase of adult trauma care: a multicenter cohort study. Ann Surg 2015;262:1123-1129

7. Hoyt BD, Coimbra BR, Potenza BB, et al. A Twelve-Year Analysis Of Disease and Provider Complications on an Organized Level I Trauma Service: As Good As it Gets? J Trauma 2003;54:26-37

8. Holbrook TL, Hoyt DB, Anderson JP. The impact of major in-hospital complications on functional outcome and quality of life after trauma. J Trauma 2001;50:91

9. Fernando DT, Berecki-Gisolf J, Newstead S, et al. Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study. BMC Public Health 2019;19:798

10. Ahmad R, Cherry RA, Lendel I, et al. Increased hospital morbidity among trauma patients with diabetes mellitus compared with age- and injury severity score–matched control subjects. Arch Surg 2007;142:613-618

11. Richmond TS, Kauder D, Strumpf N, et al. Characteristics and Outcomes of Serious Traumatic Injury in Older Adults. J Am Geriatr Soc 2002;50:215-222

12. Senn-Reeves JN, Jenkins DH. Examining the relationship between preinjury health and injury-related factors to discharge location and risk for injury-associated complications in patients after blunt thoracic trauma: a pilot study. J Trauma Nurs 2015;22:136-147

13. Morris JA, Jr, MacKenzie EJ, et al. The effect of preexisting conditions on mortality in trauma patients. JAMA 1990;263:1942-1946

14. Milzman PD, Boulanger RB, Rodriguez AA, et al. Pre-existing Disease in Trauma Patients: A Predictor of Fate Independent of Age and Injury Severity Score. J Trauma 1992;32:236-244

15. Lustenberger T, Talving P, Lam L, et al. Effect of diabetes mellitus on outcome in patients with traumatic brain injury: a national trauma databank analysis. Brain Inj 2013;27:281-285

16. Kuwabara K, Matsuda S, Imanaka Y, et al. Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database. J Trauma Acute Care 2010;68:463-470

17. Lakomkin N, Goz V, Lajam CM, et al. Higher Modified Charlson Index Scores Are Associated With Increased Incidence of Complications, Transfusion Events, and Length of Stay Following Revision Hip Arthroplasty. J Arthroplasty 2017;32:1121-1124

18. Charlson ME, Pompei P, Ales KL, et al. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis 1987;40:373-383

19. Elixhauser A, Steiner C, Harris DR, et al. Comorbidity measures for use with administrative data. Med Care 1998;36:8-27

20. Thompson HJ, Rivara FP, Nathens A, et al. Development and Validation of the Mortality Risk for Trauma Comorbidity Index. Ann Surg 2010;252:370-375

21. Toson B, Harvey LA, Close JC. The ICD-10 Charlson Comorbidity Index predicted mortality but not resource utilization following hip fracture. J Clin Epidemiol 2015;68:44-51

22. Yurkovich M, Avina-Zubieta JA, Thomas J, et al. A systematic review identifies valid comorbidity indices derived from administrative health data. J Clin Epidemiol 2015;68:3-14

23. Australian Consortium for Classification Development. The international statistical classification of diseases and related health problems, tenth revision, australian modification (ICD-10-AM/ACHI/ACS) (Tenth ed.). Darlinghurst, NSW: Independent Hospital Pricing Authority; 2012

24. Centre for Health Record Linkage. Master linkage key quality assurance report. [CheReL website]. 2012. Available at: http://www.cherel.org.au/quality-assurance. Accessed 28 June 2018,

25. AIHW:Pointer SC. Trends in hospitalised injury, Australia, 1999–00 to 2010–11. Injury research and statistics series no 86 Cat no INJCAT 162. Canberra: AIHW; 2013

26. Jackson TJ, Michel JL, Roberts RF, et al. A classification of hospital-acquired diagnoses for use with routine hospital data. Med J Aust 2009;191:544

27. Osler T, Rutledge R, Deis J, et al. ICISS: An International Classification of Disease-9 Based Injury Severity Score. J Trauma Acute Care 1996;41:380-388

28. Australian Bureau of Statistics. Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia. 2011. Available at: http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/2033.0.55.001~2011~Main%20Features~SEIFA%20Measures~10016. Accessed 04 May, 2017

29. Quan H, Sundararajan V, Halfon P, et al. Coding Algorithms for Defining Comorbidities in ICD-9-CM and ICD-10 Administrative Data. Med Care 2005;43:1130-1139

30. Sundararajan V, Henderson T, Perry C, et al. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. J Clin Epidemiol 2004;57:1288-1294

31. Quan H, Li B, Couris CM, et al. Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries. Am J Epidemiol 2011;173:676-682

32. Akaike H. A new look at the statistical model identification. IEEE Trans Automat Contr 1974;19:716-723

33. SAS Institute. Cary, NC, USA: SAS Institute Inc.; 2002-2012

34. StataCorp: College Station, TX: StataCorp LP; 2015

35. Fernando DT, Berecki-Gisolf J, Newstead S, et al. Effect of comorbidity on injury outcomes: a review of existing indices. Ann Epidemiol 2019;36:5-14

36. Klabunde CN, Potosky AL, Legler JM, et al. Development of a comorbidity index using physician claims data. J Clin Epidemiol 2000;53:1258-1267

37. Holman CAJ, Preen DB, Baynham NJ, et al. A multipurpose comorbidity scoring system performed better than the Charlson index. J Clin Epidemiol 2005;58:1006-1014

38. Martins M, Blais R. Evaluation of comorbidity indices for inpatient mortality prediction models. J Clin Epidemiol 2006;59:665-669

39. Schneeweiss S, Wang PS, Avorn J, et al. Improved comorbidity adjustment for predicting mortality in Medicare populations. Health Serv Res 2003;38:1103-1120

40. Moore L, Lavoie A, Sage NL, et al. Using Information on Preexisting Conditions to Predict Mortality From Traumatic Injury. Ann Emerg Med 2008;52:356-364.e352

41. Jackson TJ, Michel JL, Roberts R, et al. Development of a validation algorithm for 'present on admission' flagging. BMC Med Inform Decis Mak 2009;9:48

42. Michel JL, Nghiem HS, Jackson TJ. Using ICD-10-AM codes to characterise hospital-acquired complications. Health Inf Manag J 2009;38:18-25

43. Jhung MA, Banerjee SN. Administrative coding data and health care-associated infections.(Healthcare Epidemiology). Clin Infect Dis 2009;49:949

44. Independent Health Pricing Authority. Overview of Supplementary Codes for Chronic Conditions. 2015 Available at: https://ace.ihpa.gov.au/Newsletters/View.aspx?NID=3#Section_15. Accessed 11 November 2019,

45. Preen DB, Holman CDAJ, Spilsbury K, et al. Length of comorbidity lookback period affected regression model performance of administrative health data. J Clin Epidemiol 2006;59:940-946

Table 1: Characteristics of the Victorian, NSW and WA study populations

	Patients admitted[1], n (%)			
	July 2012 to June 2014, Victoria			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients	161334			
Age group (years)				
0-14 years	21240	13.2	1.4	0.01 (0.01 to 0.02)
15-24 years	23213	14.4	9.9	0.12 (0.11 to 0.12)
25-44 years	36262	22.5	13.0	0.16 (0.16 to 0.17)
45-64 years	30799	19.1	19.3	0.25 (0.25 to 0.26)
65-84 years	31390	19.5	35.9	0.54 (0.53 to 0.54)
85 and over	18430	11.4	40.0	0.62 (0.60 to 0.63)
Gender				
Male[2]	89144	55.3	16.8	0.24 (0.23 to 0.24)
Female	72190	44.7	23.5	0.33 (0.33 to 0.34)
Injury severity[3]				
Serious injury (ICISS<0.941)	20884	12.9	40.6	0.64 (0.63 to 0.65)
Other injury (ICISS>=0.941)	140450	87.1	16.7	0.22 (0.22 to 0.23)
Grouped body region				
Head/face/neck	32052	19.9	19.2	0.26 (0.25 to 0.27)
Trunk	20730	12.8	25.0	0.36 (0.35 to 0.37)
Upper extremity	54549	33.8	9.8	0.12 (0.12 to 0.13)
Lower extremity	41528	25.7	22.8	0.34 (0.33 to 0.35)
Multiple body regions	53	0.0	18.9	0.25 (0.09 to 0.40)
Unspecified body region	585	0.4	22.6	0.31 (0.26 to 0.37)
Body region not relevant	11837	7.3	47.7	0.66 (0.65 to 0.68)
Grouped injury type (first occurring)				
Superficial injury	8055	5.0	23.8	0.34 (0.32 to 0.35)
Open wound	22398	13.9	14.8	0.19 (0.18 to 0.20)
Fracture	66686	41.3	19.6	0.29 (0.28 to 0.29)
Dislocation, sprain & strain	10989	6.8	8.2	0.10 (0.10 to 0.11)

Injury to nerves & spinal cord	2038	1.3	10.4	0.13 (0.11 to 0.14)
Injury to blood vessels	1347	0.8	11.5	0.15 (0.12 to 0.17)
Injury to muscle & tendon	8451	5.2	9.1	0.11 (0.10 to 0.12)
Crushing injury	335	0.2	3.3	0.04 (0.01 to 0.06)
Traumatic amputation	1612	1.0	7.3	0.08 (0.07 to 0.10)
Eye injury- excluding foreign body	512	0.3	16.4	0.22 (0.17 to 0.27)
Intracranial injury	6416	4.0	29.4	0.43 (0.41 to 0.45)
Injury to internal organs	1762	1.1	23.5	0.32 (0.29 to 0.35)
Foreign body	2733	1.7	11.3	0.15 (0.13 to 0.16)
Burns	1879	1.2	15.1	0.21 (0.18 to 0.23)
Other and unspecified injury	14284	8.9	19.8	0.27 (0.26 to 0.28)
Systemic-poisoning/toxic effects	10536	6.5	49.5	0.68 (0.67 to 0.70)
Other effects of external cause/complication	1301	0.8	32.5	0.54 (0.48 to 0.59)
Geographic region				
Metropolitan Area	118959	73.7	19.8	0.28 (0.27 to 0.28)
Rural Area	42375	26.3	19.8	0.28 (0.27 to 0.29)
Unknown				
Outcomes				
Patients requiring an ICU stay	5285	3.3	54.3	0.89 (0.86 to 0.92)
Mean ICU-LOS[4]	85.37 (82.00 to 88.75)			
Patients requiring MV use	2495	1.6	54.7	0.85 (0.81 to 0.89)
Mean MV-LOS[5]	75.23 (70.27 to 80.19)			
Patients with at least one complication[6]	26127	16.2	42.3	0.68 (0.67 to 0.70)
Complications (median, IQR)[7]	2 (1 to 4)		2(1 to 5)	
Complications (mean, 95% CI)[7]	3.03 (2.99 to 3.06)		3.51 (3.45 to 3.57)	0.70 (0.69 to 0.71)

Table 1 (continued)

	Patients admitted[1], n (%)							
	July 2012 to June 2014, NSW				July 2012 to June 2014, WA			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients	233521				84877			
Age group (years)								

0-14 years	31730	13.6	1.5	0.02 (0.01 to 0.02)	13106	15.4	1.9	0.02 (0.02 to 0.02)
15-24 years	33888	14.5	11.0	0.13 (0.13 to 0.14)	13676	16.1	15.3	0.18 (0.17 to 0.19)
25-44 years	51737	22.2	13.5	0.17 (0.17 to 0.18)	22617	26.6	18.6	0.23 (0.22 to 0.23)
45-64 years	44501	19.1	18.3	0.25 (0.24 to 0.26)	16344	19.3	21.6	0.29 (0.28 to 0.30)
65-84 years	44948	19.2	33.2	0.51 (0.50 to 0.52)	12598	14.8	36.0	0.55 (0.54 to 0.57)
85 and over	26717	11.4	38.2	0.60 (0.59 to 0.62)	6536	7.7	41.5	0.64 (0.62 to 0.66)
Gender								
Male[2]	131598	56.4	16.2	0.23 (0.23 to 0.24)	49994	58.9	18.0	0.24 (0.24 to 0.25)
Female	101923	43.6	22.7	0.33 (0.32 to 0.33)	34883	41.1	24.0	0.33 (0.32 to 0.34)
Injury severity[3]								
Serious injury (ICISS<0.941)	30265	13.0	35.5	0.57 (0.56 to 0.59)	9566	11.3	38.3	0.60 (0.58 to 0.62)
Other injury (ICISS>=0.941)	203256	87.0	16.6	0.23 (0.23 to 0.23)	75311	88.7	18.2	0.24 (0.23 to 0.24)
Grouped body region								
Head/face/neck	48159	20.6	20.7	0.29 (0.28 to 0.29)	18350	21.6	23.7	0.31 (0.30 to 0.32)
Trunk	29199	12.5	23.1	0.34 (0.33 to 0.35)	9835	11.6	23.5	0.34 (0.33 to 0.35)
Upper extremity	77389	33.1	9.4	0.12 (0.12 to 0.13)	27833	32.8	10.9	0.14 (0.13 to 0.14)
Lower extremity	57954	24.8	19.6	0.30 (0.30 to 0.31)	20678	24.4	20.9	0.31 (0.30 to 0.32)
Multiple body regions	170	0.1	18.8	0.26 (0.17 to 0.35)	51	0.1	25.5	0.31 (0.15 to 0.47)
Unspecified body region	1247	0.5	22.3	0.34 (0.30 to 0.38)	376	0.4	22.1	0.30 (0.23 to 0.36)
Body region not relevant	19403	8.3	45.5	0.65 (0.64 to 0.66)	7754	9.1	41.6	0.56 (0.55 to 0.58)
Grouped injury type (first occurring)								
Superficial injury	14875	6.4	22.6	0.33 (0.32 to 0.34)	4659	5.5	27.7	0.37 (0.35 to 0.39)
Open wound	35691	15.3	16.9	0.23 (0.22 to 0.23)	12623	14.9	20.6	0.27 (0.26 to 0.28)
Fracture	94258	40.4	17.3	0.26 (0.26 to 0.27)	30714	36.2	18.5	0.27 (0.26 to 0.27)
Dislocation, sprain & strain	13330	5.7	6.6	0.09 (0.08 to 0.09)	6755	8.0	7.5	0.09 (0.08 to 0.10)
Injury to nerves & spinal cord	2559	1.1	8.6	0.11 (0.10 to 0.13)	1147	1.4	11.1	0.14 (0.11 to 0.16)
Injury to blood vessels	1096	0.5	15.0	0.19 (0.16 to 0.22)	650	0.8	18.5	0.23 (0.19 to 0.28)
Injury to muscle & tendon	10921	4.7	6.7	0.08 (0.08 to 0.09)	5423	6.4	10.1	0.12 (0.11 to 0.13)
Crushing injury	469	0.2	3.4	0.04 (0.02 to 0.06)	166	0.2	4.2	0.05 (0.01 to 0.08)
Traumatic amputation	1622	0.7	6.8	0.08 (0.06 to 0.10)	747	0.9	7.9	0.09 (0.07 to 0.11)
Eye injury- excluding foreign body	919	0.4	17.3	0.22 (0.19 to 0.26)	308	0.4	19.5	0.23 (0.17 to 0.28)
Intracranial injury	9355	4.0	28.1	0.42 (0.41 to 0.44)	3385	4.0	30.6	0.44 (0.41 to 0.47)

Injury to internal organs	2198	0.9	22.5	0.32 (0.29 to 0.35)	1066	1.3	23.7	0.34 (0.29 to 0.38)
Foreign body	3947	1.7	9.2	0.12 (0.10 to 0.13)	1486	1.8	9.6	0.12 (0.10 to 0.14)
Burns	3244	1.4	8.8	0.12 (0.10 to 0.14)	1660	2.0	14.3	0.20 (0.17 to 0.22)
Other and unspecified injury	19634	8.4	19.6	0.28 (0.27 to 0.29)	6334	7.5	22.8	0.30 (0.29 to 0.32)
Systemic-poisoning/toxic effects	17162	7.3	47.8	0.67 (0.66 to 0.68)	6866	8.1	43.5	0.59 (0.57 to 0.60)
Other effects of external	2241	1.0	28.2	0.47 (0.43 to 0.50)	888	1.0	26.7	0.40 (0.35 to 0.45)
Geographic region								
Metropolitan Area	158595	67.9	18.9	0.28 (0.27 to 0.28)	60151	70.9	19.7	0.27 (0.27 to 0.28)
Rural Area	74918	32.1	19.2	0.27 (0.26 to 0.27)	24405	28.8	22.1	0.29 (0.28 to 0.30)
Unknown	8	0.0	*	0.25 (-0.07 to 0.57)	321	0.4	34.6	0.42 (0.35 to 0.50)
Outcomes								
Patients requiring an ICU stay	7000	3.0	45.1	0.78 (0.75 to 0.81)	774	0.9	58.0	1.02 (0.93 to 1.10)
Mean ICU-LOS[4]	111.71 (98.16 to 125.27)				85.37 (82.00 to 88.75)			
Patients requiring MV use	3300	1.4	44.5	0.73 (0.69 to 0.76)	1136	1.6	60.2	0.96 (0.89 to 1.02)
Mean MV-LOS[5]	86.07 (73.76 to 98.37)				75.23 (70.27 to 80.19)			
Patients with at least one complication	16277	7.0	48.8	0.85 (0.83 to 0.86)	7879	9.3	43.3	0.73 (0.71 to 0.75)
Complications (median, IQR)[7]	2 (1 to 3)		2 (1 to 3)		2 (1 to 3)		2 (1 to 4)	
Complications (mean, 95% CI)[7]	2.79 (2.75 to 2.83)		3.08 (3.02 to 3.14)	0.86 (0.84 to 0.88)	2.60 (2.54 to 2.66)		3.00 (2.91 to 3.10)	0.76 (0.74 to 0.78)

Notes:

1. Index injury admissions to all public and private hospitals, limited to residents within the relevant state
2. Intersex/intermediate/unstated sex patient counts less than 5 added to the majority sex group to protect confidentiality
3. Worst injury method-ICD-based Injury Severity Score less than or equal to 0.941 considered as serious injury
4. Includes only patients requiring an ICU stay, excludes children
5. Includes only patients requiring an MV use, excludes children
6. Total patients=161331 for Victoria
7. Includes only patients with at least one complication, excludes children

*Cell count 1-4 suppressed to protect confidentiality

Table 2: Presence of comorbidity and the mean LOS in the ICU and MV, and the mean number of complications (Victoria, ages 15 years and over)

Comorbidity	Index admissions (N=140094), n (%)	ICU stay hours for those[1] using the ICU, mean (CI)	MV use hours for those[2] on the MV, mean (CI)	Complications for those with at least one[3], mean (CI)
HIV/AIDS	54 (0.0)	156.6 (-24.1 to 337.3)	135.6 (-123.1 to 394.3)	3.3 (1.5 to 5.0)
Alcohol dependence	6425 (4.6)	76.8 (68.1 to 85.4)	52.4 (41.8 to 63.0)	3.0 (2.9 to 3.2)
Drug dependence	1496 (1.1)	69.8 (61.4 to 78.3)	41.8 (33.1 to 50.6)	2.9 (2.6 to 3.2)
Any malignancy	706 (0.5)	60.0 (45.6 to 74.4)	43.1 (22.0 to 64.1)	3.6 (3.2 to 3.9)
Blood loss anaemia	170 (0.1)	82.1 (59.6 to 104.7)	61.8 (17.9 to 105.7)	3.6 (3.0 to 4.1)
Cardiac arrhythmias	3775 (2.7)	85.6 (74.9 to 96.3)	82.2 (57.6 to 106.8)	3.9 (3.7 to 4.1)
Cerebrovascular disease	602 (0.4)	123.7 (81.3 to 166.0)	120.1 (59.8 to 180.4)	3.6 (3.2 to 4.0)
Chronic pulmonary disease	1302 (0.9)	106.7 (87.7 to 125.8)	94.3 (62.0 to 126.5)	4.4 (4.1 to 4.7)
Coagulopathy	1133 (0.8)	120.3 (98.5 to 142.1)	129.3 (96.6 to 162.0)	3.9 (3.6 to 4.2)
Congestive heart failure	1257 (0.9)	91.4 (78.5 to 104.3)	65.5 (45.9 to 85.0)	4.4 (4.2 to 4.7)
Deficiency anaemias	578 (0.4)	71.5 (47.9 to 95.1)	64.5 (9.0 to 120.1)	3.1 (2.8 to 3.4)
Dementia	2889 (2.1)	61.4 (49.3 to 73.6)	76.9 (37.1 to 116.8)	3.1 (3.0 to 3.3)
Depression	2966 (2.1)	70.6 (59.9 to 81.3)	46.0 (36.1 to 56.0)	2.9 (2.7 to 3.1)
Diabetes with chronic complications	4243 (3.0)	99.8 (85.6 to 113.9)	98.7 (73.4 to 124.0)	3.8 (3.7 to 4.0)
Diabetes without complications	8969 (6.4)	94.0 (79.3 to 108.7)	81.7 (62.9 to 100.4)	3.3 (3.2 to 3.4)
Hemiplegia/paraplegia	538 (0.4)	105.6 (81.7 to 129.5)	90.2 (64.7 to 115.8)	3.6 (3.2 to 4.0)
Hypertension complicated	54 (0.0)	36.7 (14.0 to 59.4)	*	4.5 (3.3 to 5.6)
Hypertension uncomplicated	4510 (3.2)	101.1 (90.8 to 111.4)	81.2 (67.5 to 94.9)	4.1 (4.0 to 4.3)
Hypothyroidism	152 (0.1)	81.2 (47.7 to 114.7)	*	3.9 (3.2 to 4.6)
Metastatic solid tumor	380 (0.3)	61.5 (38.9 to 84.1)	29.4 (-0.6 to 59.4)	3.3 (2.9 to 3.7)
Mild liver disease	1167 (0.8)	87.6 (72.5 to 102.6)	69.2 (51.4 to 87.0)	3.6 (3.2 to 3.9)
Moderate or severe liver disease	116 (0.1)	113.4 (74.6 to 152.3)	107.8 (48.2 to 167.4)	4.7 (3.8 to 5.7)
Myocardial infarction	248 (0.2)	104.7 (60.5 to 148.9)	100.6 (32.4 to 168.8)	4.1 (3.5 to 4.6)
Obesity	229 (0.2)	142.4 (92.1 to 192.7)	174.8 (66.9 to 282.6)	4.5 (3.7 to 5.3)
Peptic ulcer disease	84 (0.1)	117.5 (60.0 to 175.1)	82.6 (33.6 to 131.6)	4.3 (3.3 to 5.4)
Peripheral vascular disease	702 (0.5)	124.5 (90.2 to 158.8)	122.8 (83.1 to 162.5)	3.7 (3.3 to 4.2)
Psychoses	568 (0.4)	82.8 (67.4 to 98.2)	55.2 (34.6 to 75.8)	3.3 (2.8 to 3.7)
Pulmonary circulation disorders	133 (0.1)	119.4 (82.6 to 156.1)	88.0 (30.7 to 145.3)	4.5 (3.7 to 5.3)
Renal disease including renal failure	3402 (2.4)	81.2 (72.0 to 90.5)	61.8 (45.7 to 77.9)	4.1 (4.0 to 4.3)
Rheumatic disease including some other connective tissue disorders	177 (0.1)	103.8 (71.5 to 136.0)	76.8 (14.3 to 139.4)	3.8 (3.1 to 4.5)
Valvular disease	326 (0.2)	85.8 (58.1 to 113.6)	98.0 (49.2 to 146.8)	4.8 (4.3 to 5.3)

Notes:

*Cell count 1-4 suppressed to protect confidentiality

1. n=5116
2. n=2413
3. n=23693

Table 3: Presence of comorbidity with CHADx complications (Victoria, age 15 years and over)

Comorbidity	CHADx group number																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intra and post procedural	Adverse drug events	Accidental injuries	Specific infections	Cardiovascular	Respiratory	Gastrointestinal	Skin conditions	Genitourinary	Hospital-acquired psychiatric states	Early pregnancy	Labour, delivery & postpartum	Perinatal	Haematological disorders	Metabolic disorders	Nervous system	Other
HIV/AIDS	*	*	*	*	*	*	0.1	0.1	*	*	*	*	*	*	*	*	0.1
Alcohol dependence	4.7	3.6	5.2	5.9	4.1	5.5	3.7	4.4	3.5	6.6	0.0	0.0	0.0	4.5	5.8	7.3	5.0
Drug dependence	1.5	1.2	1.3	1.1	1.4	1.6	0.9	0.8	1.0	2.4	0.0	0.0	0.0	1.0	1.4	3.4	1.3
Any malignancy	1.2	1.4	2.0	2.3	1.4	2.2	1.7	1.5	1.5	1.8	0.0	0.0	0.0	2.0	1.7	1.9	1.7
Blood loss anaemia	0.5	0.4	0.4	0.4	0.5	0.4	0.5	0.6	0.6	0.6	0.0	0.0	0.0	*	0.5	0.9	0.5
Cardiac arrhythmias	7.1	8.1	9.6	9.6	9.7	10.1	7.4	8.9	9.9	10.2	0.0	0.0	0.0	9.5	10.5	7.3	7.7
Cerebrovascular disease	1.1	0.9	2.2	2.1	1.3	1.6	1.3	1.3	1.5	1.4	0.0	0.0	0.0	1.1	1.6	2.3	1.4
Chronic pulmonary disease	2.7	4.1	4.2	5.8	3.9	7.1	3.4	3.5	3.7	4.1	0.0	0.0	0.0	3.8	4.7	3.0	3.0
Coagulopathy	2.1	2.3	2.3	3.6	2.4	2.6	1.9	2.4	2.3	2.4	0.0	0.0	0.0	2.6	2.9	3.1	2.4
Congestive heart failure	2.8	4.6	4.1	6.3	4.7	6.7	3.3	4.2	5.2	4.6	0.0	0.0	0.0	4.1	5.0	2.4	3.1
Deficiency anaemias	1.1	1.3	1.4	1.7	1.1	1.2	1.3	1.6	1.4	1.1	0.0	0.0	0.0	0.5	1.7	1.9	1.1
Dementia	4.4	4.2	8.7	6.0	6.2	6.4	4.9	6.0	8.1	7.7	0.0	0.0	0.0	8.0	7.2	3.5	4.7
Depression	1.8	2.7	2.8	3.0	2.2	2.7	2.3	1.9	2.1	3.8	0.0	0.0	0.0	1.3	3.1	4.1	3.1
Diabetes with chronic complications	6.3	9.3	9.9	11.1	8.1	9.5	8.6	9.2	10.4	9.2	0.0	0.0	0.0	9.2	10.2	8.1	8.1
Diabetes without complications	8.8	10.6	12.1	13.6	9.7	10.9	10.7	11.6	11.3	11.0	0.0	0.0	0.0	10.6	11.9	9.8	10.3
Hemiplegia/paraplegia	0.9	0.9	2.2	2.0	1.3	1.3	1.1	1.3	1.4	1.1	0.0	0.0	0.0	1.0	1.4	2.0	1.3
Hypertension complicated	0.2	0.2	*	*	0.2	0.2	0.2	0.2	0.2	0.2	0.0	0.0	0.0	0.3	0.3	*	0.2
Hypertension uncomplicated	8.5	12.1	14.4	14.4	13.6	12.4	11.1	12.1	14.1	13.8	0.0	0.0	0.0	13.5	15.0	13.9	11.5
Hypothyroidism	0.3	0.5	0.4	0.5	0.4	0.3	0.4	0.5	0.4	0.5	0.0	0.0	0.0	0.4	0.5	*	0.4
Metastatic solid tumor	0.6	0.5	0.9	1.2	0.6	1.2	0.8	0.7	0.7	0.9	0.0	0.0	0.0	1.2	0.7	0.7	1.0
Mild liver disease	1.4	1.5	1.3	1.5	1.4	1.6	1.2	1.3	1.2	1.9	0.0	0.0	0.0	1.7	1.8	2.9	1.6
Moderate or severe liver disease	0.3	0.2	*	0.7	0.4	0.4	0.3	0.5	0.3	0.5	0.0	0.0	0.0	0.6	0.6	0.8	0.3
Myocardial infarction	0.5	0.5	1.0	0.9	1.0	0.8	0.7	0.9	0.8	0.9	0.0	0.0	0.0	0.8	0.9	0.7	0.5
Obesity	0.7	0.7	0.4	0.8	0.5	0.8	0.5	0.7	0.7	0.6	0.0	0.0	0.0	0.4	0.6	0.8	0.6
Peptic ulcer disease	0.2	0.1	0.4	0.2	0.2	0.3	0.1	0.3	0.1	0.2	0.0	0.0	0.0	0.2	0.2	0.5	0.2
Peripheral vascular disease	1.6	*	1.3	*	1.1	1.1	1.0	1.6	1.0	0.9	0.0	0.0	0.0	1.2	1.1	*	1.2
Psychoses	0.8	0.7	1.1	1.6	0.9	1.3	0.6	0.7	0.6	1.3	0.0	0.0	0.0	0.8	1.0	1.6	1.0

Comorbidity	CHADx group number																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	Intra and post procedural	Adverse drug events	Accidental injuries	Specific infections	Cardiovascular	Respiratory	Gastrointestinal	Skin conditions	Genitourinary	Hospital-acquired psychiatric states	Early pregnancy	Labour, delivery & postpartum	Perinatal	Haematological disorders	Metabolic disorders	Nervous system	Other
Pulmonary circulation disorders	0.4	0.4	*	0.7	0.5	0.7	0.4	0.5	0.5	0.3	0.0	0.0	0.0	0.4	0.5	0.8	0.4
Renal disease including renal failure	6.2	9.9	11.5	11.9	9.5	9.7	9.2	9.9	11.5	10.1	0.0	0.0	0.0	11.7	12.2	7.1	8.0
Rheumatic disease including some other connective tissue disorders	0.3	0.6	0.6	0.9	0.3	0.5	0.6	0.5	0.4	0.3	0.0	0.0	0.0	0.5	0.4	*	0.4
Valvular disease	1.0	1.1	1.6	1.3	1.3	1.6	1.0	1.5	1.3	1.1	0.0	0.0	0.0	1.4	1.5	1.0	1.2

Table 4: Performance of selected comorbidity measures in assessing the association between comorbidity and selected outcome measures (Victoria)

Model	Ln (ICU hours)[1]		Ln (MV hours)[2]		Number of complications[3]	
	Adjusted R^2	Model fit AIC	Adjusted R^2	Model fit AIC	Mc. Fadden's Adjusted R^2	Model fit AIC
(i) Baseline model	0.104	14591	0.145	7815	0.029	106849
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.121	14498	0.164	7763	0.036	106142
(iii) Baseline model + selected comorbidities (modelled as a weighted summed score)[4]	0.121	14492	0.152	7795	0.032	106584
(iv) Baseline model + comorbidity using CCI weights	0.108	14572	0.147	7809	0.031	106639
(v) Baseline model + comorbidity using Quan weights	0.107	14577	0.147	7810	0.030	106720
(vi) Baseline model + ECM	0.130	14471	0.178	7752	0.036	106103

Notes:

1. Baseline model includes age, sex, injury severity, injury type and body region; outcome =ICU stay hours (Ln transformed linear model)
2. Baseline model includes age, sex and injury severity; outcome= MV hours (Ln transformed linear model)
3. Baseline model includes age, sex, injury type, injury severity and body region; outcome=number of complications for those with at least one complication (negative binomial model)
4. See Methods for weight calculation, excludes weights resulting from an OR<1.2, rounded weights used,

Note: See Table 5 for selected comorbidities for each outcome

Table 5: Risk adjusted beta coefficients, incident rate ratios, and suggested weights for ICU and MV hours and complications among Victorian hospital-admitted injury patients

	ICU hours		MV hours		Number of CHADx complications		CCI	Updated CCI per Quan et al. (2011)	ECM point scores per van Walraven et al. (2009)
	Beta coefficient (95% CI)	Index weight[1]	Beta coefficient (95% CI)	Index weight[1]	IRR (95% CI)	Index weight[2]			
Age groups									
15-24 years	-0.13 (-0.23 to -0.03)		-0.33 (-0.49 to -0.17)		0.69 (0.66 to 0.73)				
25-44 years	-0.03 (-0.11 to 0.06)		-0.16 (-0.31 to -0.02)		0.73 (0.70 to 0.75)				
45-64 years	0.05 (-0.03 to 0.13)		0.12 (-0.03 to 0.27)		0.79 (0.77 to 0.82)				
65-84 years	Reference group		Reference group		Reference group				
85+ years	-0.26 (-0.36 to -0.16)		-0.53 (-0.81 to -0.25)		1.08 (1.06 to 1.11)				
Female gender	-0.03 (-0.08 to 0.03)		-0.04 (-0.14 to 0.06)		0.97 (0.95 to 0.99)				
Serious injury	0.43 (0.35 to 0.51)		0.87 (0.77 to 0.97)		1.38 (1.34 to 1.41)				
Comorbidity									
HIV/AIDS	-	-	-	-	-	-	6	4	0
Alcohol dependence	-	-	-0.36 (-0.48 to -0.24)*	-	1.12 (1.07 to 1.17)*	-	#	#	0
Drug dependence	-	-	-	-	-	-	#	#	-7
Any malignancy	-	-	-	-	-	-	2	2	4
Blood loss anaemia	-	-	-	-	-	-	#	#	-2
Cardiac arrhythmias	-	-	-	-	1.10 (1.06 to 1.14)*	-	#	#	5
Cerebrovascular disease	-	-	-	-	-	-	1	0	##
Chronic pulmonary disease	0.28 (0.14 to 0.41)	1	-	-	1.27 (1.20 to 1.34)	1	1	1	3
Coagulopathy	0.34 (0.19 to 0.50)	1	0.65 (0.38 to 0.93)	2	1.16 (1.09 to 1.24)*	-	#	#	3
Congestive heart failure	-	-	-	-	1.17 (1.11 to 1.24)*	-	1	2	7
Deficiency anaemias	-	-	-	-	-	-	#	#	-2
Dementia	-	-	-	-	0.85 (0.81 to 0.88)*	-	1	2	##
Depression	0.21 (0.12 to 0.31)	1	-	-	1.15 (1.07 to 1.23)*	-	#	#	-3

	ICU hours		MV hours		Number of CHADx complications		CCI	Updated CCI per Quan et al. (2011)	ECM point scores per van Walraven et al. (2009)
	Beta coefficient (95% CI)	Index weight[1]	Beta coefficient (95% CI)	Index weight[1]	IRR (95% CI)	Index weight[2]			
Diabetes with chronic complications	-	-	-	-	1.09 (1.05 to 1.13)*	-	2	1	0
Diabetes without complications	-	-	-	-	-	-	1	0	0
Hemiplegia/paraplegia	-	-	-	-	-	-	2	2	7
Hypertension complicated	-	-	-	-	-	-	#	#	0
Hypertension uncomplicated	0.26 (0.17 to 0.36)	1	-	-	1.17 (1.13 to 1.21)*	-	#	#	0
Hypothyroidism	-	-	-	-	-	-	#	#	0
Metastatic solid tumor	-	-	-	-	-	-	6	6	12
Mild liver disease	-	-	-	-	-	-	1	2	11
Moderate or severe liver disease	-	-	-	-	1.64 (1.38 to 1.94)	2	3	4	11
Myocardial infarction	-	-	-	-	-	-	1	0	##
Obesity	0.62 (0.33 to 0.92)	2	-	-	1.57 (1.37 to 1.80)	2	#	#	-4
Peptic ulcer disease	-	-	-	-	-	-	1	0	0
Peripheral vascular disease	-	-	-	-	1.18 (1.08 to 1.30)*	-	1	0	2
Psychoses	-	-	-	-	1.29 (1.16 to 1.43)	1	#	#	0
Pulmonary circulation disorders	-	-	-	-	-	-	#	#	4
Renal disease including renal failure	-	-	-	-	1.09 (1.05 to 1.14)*	-	2	1	5
Rheumatic disease including some other connective tissue disorders	-	-	-	-	-	-	1	1	0
Valvular disease	-	-	-	-	1.23 (1.12 to 1.36)	1	#	#	-1

Notes:
- Condition not significantly associated with outcome
Not included in CCI list
Not included in ECM list
*Excluded from weighted index as OR<1.2
1 Weight=exp(beta) (see methods for details)

2 Weight= IRR (see methods for details)

Table A1: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (Victoria)

Model	Outcome					
	Ln (ICU hours)[1]		Ln (MV hours)[2]		Number of complications[3]	
	Adjusted R^2	Model fit AIC	Adjusted R^2	Model fit AIC	Mc.Fadden's Adjusted R^2	Model fit AIC
(viii) Baseline model + presence of at least one comorbidity	0.110	14558	0.145	7817	0.032	106532
(ix) Baseline model + count of comorbidities	0.115	14530	0.145	7815	0.033	106461
(x) Baseline model + individual comorbidity (all 31 conditions)	0.125	14503	0.175	7758	0.036	106128
(xi) Baseline model + selected comorbidities (modelled as a weighted summed score)[4]	0.121	14494	0.152	7795	0.032	106594
Baseline model deconstructed						
Age	0.011	15073	0.027	8124	0.011	108842
Age + Sex	0.017	15047	0.032	8114	0.012	108799
Age + Sex + Body region	0.066	14788			0.015	108381
Age + Sex + Body region + Injury type	0.087	14686			0.024	107476
Age + Sex + Body region + Injury type + Injury severity	0.104	14591	0.145	7815	0.029	106848.6

Notes:

1. Baseline model includes age, sex, injury severity, injury type and body region; outcome =ICU stay hours (Ln transformed linear model)
2. Baseline model includes age, sex and injury severity; outcome= MV hours (Ln transformed linear model)
3. Baseline model includes age, sex, injury type, injury severity and body region; outcome=number of complications for those with at least one complication (negative binomial model)
4. Actual ORs used as weights, excludes weights resulting from an OR<1.2

Table A2: Performance of selected comorbidity measures in assessing the association between comorbidity and selected outcome measures (Victoria)

Model	CHADx7[1] (gastrointestinal complications)		CHADx5[2] (cardiovascular complications)		CHADx15[3] (metabolic disorders)	
	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC	AUC (95% CI)	Model fit AIC
(i) Baseline model	0.600 (0.593 to 0.608)	31123	0.603 (0.595 to 0.610)	29778	0.651 (0.643 to 0.658)	27516
(ii) Baseline model + selected comorbidities (individually modelled with binary representation)	0.605 (0.598 to 0.613)	31060	0.612 (0.605 to 0.620)	29633	0.668 (0.661 to 0.675)	27216
(iv) Baseline model + comorbidity using CCI weights	0.601 (0.594 to 0.609)	31109	0.603 (0.595 to 0.611)	29774	0.659 (0.652 to 0.666)	27399
(vi) Baseline model + ECM	0.604 (0.597 to 0.611)	31120	0.603 (0.595 to 0.610)	29778	0.674 (0.667 to 0.681)	27140

Notes:

1. Baseline model includes age, sex, injury type, body region and SEIFA; outcome= presence of CHADx7 (logistic model)
2. Baseline model includes age, sex, injury severity, injury type, body region and geographic region; outcome =presence of CHADx5 (logistic model)
3. Baseline model includes age, sex, injury type, injury severity, body region and geographic region; outcome= presence of CHADx15 (logistic model)

See Table A3 for selected comorbidities for each outcome

Table A3: Conditions included in the injury comorbidity indices for ICU stay, MV use, complications, CCI and ECM

Comorbidity	Outcome							
	ICU hours (AICI-icu)[1]	MV hours (AICI-mv)[2]	Complications (AICI-comp)[3]	Gastrointestinal complications	Cardiovascular complications	Metabolic disorders	CCI	ECM
HIV/AIDS	X	X	X	X	X	X	✓	✓
Alcohol dependence	X	✓	✓	X	X	✓	X	✓
Drug dependence	X	X	X	X	X	X	X	✓
Any malignancy	X	X	X	X	X	X	✓[4]	✓[5]
Blood loss anaemia	X	X	X	X	X	X	X	✓
Cardiac arrhythmias	X	X	✓	X	✓	✓	X	✓
Cerebrovascular disease	X	X	X	X	X	X	✓	X
Chronic pulmonary disease	✓	X	✓	X	✓	✓	✓	✓
Coagulopathy	✓	✓	✓	X	X	X	X	✓
Congestive heart failure	X	X	✓	X	✓	X	✓	✓
Deficiency anaemias	X	X	X	X	X	X	X	✓
Dementia	X	X	✓	✓	X	X	✓	X
Depression	✓	X	✓	X	X	X	X	✓
Diabetes with chronic complications	X	X	✓	X	X	X	✓	✓
Diabetes without complications	X	X	X	X	X	X	✓	✓
Fluid and electrolyte disorders	-	-	-	-	-	-	X	✓
Hemiplegia/paraplegia	X	X	X	X	X	X	✓	✓
Hypertension complicated	X	X	X	X	X	X	X	✓
Hypertension uncomplicated	✓	X	✓	X	✓	✓	X	
Hypothyroidism	X	X	X	X	X	X	X	✓
Metastatic solid tumor	X	X	X	X	X	X	✓	✓
Mild liver disease	X	X	X	X	X	X	✓	✓
Moderate or severe liver disease	X	X	✓	X	X	✓	✓	
Myocardial infarction	X	X	X	X	X	X	✓	X
Obesity	✓	X	✓	X	X	X	X	✓
Other neurological disorders	-	-	-	-	-	-	X	✓
Peptic ulcer disease	X	X	X	X	X	X	✓	✓
Peripheral vascular disease	X	X	✓	X	X	X	✓	✓
Psychoses	X	X	✓	X	X	X	X	✓
Pulmonary circulation disorders	X	X	X	X	X	X	X	✓

Renal disease including renal failure	X	X	✓	✓	X	✓	✓	✓
Rheumatic disease including some other connective tissue disorders	X	X	X	X	X	X	✓	✓
Valvular disease	X	X	✓	X	X	✓	X	✓
Weight loss	-	-	-	-	-	-	X	✓

Notes:
1. AICI-icu - Australian Injury Comorbidity Index - ICU hours
2. AICI-mv - Australian Injury Comorbidity Index - MV hours
3. AICI-comp - Australian Injury Comorbidity Index -hospital acquired complications
4. Includes lymphoma, solid tumors without metastasis and leukaemia
5. Includes lymphoma and solid tumors without metastasis

Table A4: Performance of new comorbidity indices vs existing comorbidity indices in injury sub-groups (Victoria)

Model	Ln (ICU hours)					
	Adults (25-64 years)		Severe injury (adults)		Intracranial injury[1] (adults)	
	Adjusted R2	Model fit AIC	Adjusted R2	Model fit AIC	Adjusted R2	Model fit AIC
Baseline model[2]	0.134	7097	0.080	7826	0.111	1855
Baseline model + AICI-icu	0.157	7035	0.086	7813	0.129	1847
Baseline model + comorbidity using CCI weights	0.145	7068	0.080	7827	0.110	1856
Baseline model + comorbidity using ECM	0.180	6991	0.089	7831	0.114	1880
	Number of complications					
	Older adults (>=65 years)		Severe injury (adults)		Intracranial injury[1] (adults)	
	Mc.Fadden's Adjusted R2	Model fit AIC	Mc.Fadden's Adjusted R2	Model fit AIC	Mc.Fadden's Adjusted R2	Model fit AIC
Baseline model[3]	0.014	75988	0.004	52637.56	0.010	6333
Baseline model + AICI-comp	0.020	75511	0.010	52335.84	0.009	6335
Baseline model + comorbidity using CCI weights	0.015	75853	0.005	52589.38	0.009	6335
Baseline model + comorbidity using ECM	0.020	75502	0.009	52351.63	0.007	6350

Notes:

1. Intracranial injury = ICD-10-AM codes S06.00 - S06.9
2. Baseline model includes age, sex, injury severity, injury type and body region; outcome =ICU stay hours (ln transformed linear model)
3. Baseline model includes age, sex, injury severity, injury type and body region; outcome=grouped number of complications (negative binomial model)

Table A4 continued

Model	Ln (ICU hours)					
	Hip-fracture[1]		Blunt trauma[2]		Penetrating trauma[3]	
	Adjusted R2	Model fit AIC	Adjusted R2	Model fit AIC	Adjusted R2	Model fit AIC
Baseline model[4]	0.005	1761	0.103	8995	0.256	443
Baseline model + AICI-icu	0.004	1766	0.114	8963	0.251	448
Baseline model + comorbidity using CCI weights	0.004	1763	0.105	8988	0.251	445
Baseline model + comorbidity using ECM	0.046	1764	0.118	8976	0.243	460
	Number of complications					
	Hip-fracture[1]		Blunt trauma[2]		Penetrating trauma[3]	
	Mc.Fadden's Adjusted R2	Model fit AIC	Mc.Fadden's Adjusted R2	Model fit AIC	Mc.Fadden's Adjusted R2	Model fit AIC
Baseline model[5]	0.000	28490	0.026	92438	0.048	2331
Baseline model + AICI-comp	0.006	28296	0.033	91806	0.057	2305
Baseline model + comorbidity using CCI weights	0.001	28462	0.029	92224	0.048	2331
Baseline model + comorbidity using ECM	0.005	28327	0.033	91785	0.046	2317

Notes:
1. Hip fractures = ICD-10 codes S72.0 - S72.2, >= 45 years of age
2. Blunt trauma = ICD-10 codes V00-V99, W00-W19, W20-W24, W30-W31, W50-W52, X50, X79-X82, Y00-Y05 and Y29-Y32
3. Penetrating trauma = ICD-10 codes W53, W54, W55, W57, W58, W59, W25, W26, W27, W28, W29, W45, W32, W34, X72-X74, X78, X93-X95, X99, Y22-Y24 andY28
4. Baseline model includes age, sex, injury severity, injury type and body region; outcome =ICU stay hours (ln transformed linear model)
5. Baseline model includes age, sex, injury severity, injury type and body region; outcome=grouped number of complications (negative binomial model)

Table A5: Socio Economic Index for Areas (SEIFA) and country of birth details for the Victorian, NSW and WA study populations

	Patients admitted1, n (%)											
	July 2012 to June 2014, Victoria				July 2012 to June 2014, NSW				July 2012 to June 2014, WA			
	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)	n	%	At least one comorbidity (%)	Count of comorbidities, mean (95% CI)
Total patients	161334				233521				84877			
SEIFA state decile[1]												
1	17503	10.8	21.6	0.31 (0.30 to 0.32)	17879	7.7	20.1	0.29 (0.28 to 0.30)	1800	2.1	36.2	0.46 (0.43 to 0.49)
2	**	**	20.3	0.28 (0.27 to 0.30)	11249	4.8	19.7	0.29 (0.27 to 0.30)	2359	2.8	25.5	0.33 (0.31 to 0.36)
3	10595	6.5	22.0	0.32 (0.31 to 0.33)	12527	5.4	22.4	0.32 (0.31 to 0.34)	1813	2.1	22.0	0.29 (0.26 to 0.31)
4	17975	11.1	21.1	0.29 (0.28 to 0.30)	21142	9.1	21.6	0.31 (0.30 to 0.32)	5713	6.7	22.7	0.31 (0.29 to 0.33)
5	10601	6.6	17.6	0.25 (0.24 to 0.26)	20382	8.7	18.3	0.26 (0.25 to 0.27)	5656	6.7	21.4	0.29 (0.28 to 0.31)
6	11830	7.3	18.8	0.27 (0.25 to 0.28)	30030	12.9	18.7	0.27 (0.26 to 0.28)	4759	5.6	20.5	0.29 (0.27 to 0.31)
7	11678	7.3	20.0	0.28 (0.27 to 0.29)	24255	10.4	18.9	0.27 (0.26 to 0.28)	10226	12.0	18.2	0.25 (0.24 to 0.26)
8	25726	16.0	18.9	0.26 (0.26 to 0.27)	24339	10.4	17.6	0.25 (0.24 to 0.26)	10719	12.6	20.8	0.29 (0.28 to 0.30)
9	23873	14.8	19.6	0.27 (0.27 to 0.28)	31664	13.6	19.2	0.28 (0.28 to 0.29)	24734	29.1	19.3	0.26 (0.25 to 0.27)
10	22902	14.2	18.7	0.26 (0.25 to 0.27)	38996	16.7	16.9	0.25 (0.24 to 0.25)	16777	19.8	19.2	0.26 (0.25 to 0.27)
999	*	*	*	*	1058	0.5	33.9	0.45 (0.40 to 0.49)	321	0.4	34.6	0.42 (0.35 to 0.50)
Country of birth												
Australia	121134	75.4	17.5	0.24 (0.24 to 0.24)	178833	76.6	17.6	0.25 (0.25 to 0.25)	60205	70.9	19.7	0.26 (0.26 to 0.27)
New Zealand	2397	1.5	13.8	0.18 (0.16 to 0.20)	4126	1.8	16.5	0.23 (0.21 to 0.25)	3173	3.7	15.5	0.19 (0.17 to 0.21)
England	4912	3.0	27.8	0.40 (0.38 to 0.42)	8043	3.4	24.6	0.36 (0.34 to 0.37)	6185	7.3	25.1	0.37 (0.35 to 0.39)
Italy	3474	2.0	42.7	0.68 (0.65 to 0.71)	2689	1.2	39.3	0.64 (0.60 to 0.67)	1056	1.2	39.6	0.62 (0.56 to 0.68)
Greece	2162	1.3	40.0	0.62 (0.58 to 0.66)	1642	0.7	40.6	0.67 (0.62 to 0.72)	147	0.2	44.9	0.72 (0.55 to 0.89)
India	1657	1.1	16.4	0.22 (0.19 to 0.24)	1607	0.7	15.6	0.22 (0.19 to 0.25)	699	0.8	26.9	0.41 (0.35 to 0.48)
All other	25598	15.8	25.0	0.36 (0.35 to 0.37)	36581	15.7	22.7	0.34 (0.34 to 0.35)	13412	15.8	20.4	0.29 (0.27 to 0.30)

Notes:

1. Based on SLAs for Victoria and NSW, and LGAs for WA
*Cell count 1-4 suppressed to protect confidentiality
** Secondary cell suppression to maintain confidentiality of groups with 1-4 cases

Table A6: Presence of comorbidity with the mean LOS in the ICU and MV, and the mean number of complications (NSW and WA, age 15 years and over)

Comorbidity	NSW			WA		
	Index admissions (N=201791), n (%)	ICU stay hours for those using1 the ICU, mean (CI)	Complications for those with at least one, mean (CI)	Index admissions (N=71771), n (%)	ICU stay hours for those2 using the ICU, mean (CI)	Complications for those with at least one, mean (CI)
HIV/AIDS	49 (0.0)	81.3 (-44.2 to 206.7)	*	24 (0.0)	*	*
Alcohol dependence	10970 (5.4)	76.7 (68.2 to 85.3)	2.5 (2.4 to 2.7)	6307 (8.8)	71.5 (57.1 to 86.0)	2.5 (2.3 to 2.8)
Drug dependence	3108 (1.5)	78.9 (63.8 to 94.0)	2.5 (2.1 to 2.8)	1347 (1.9)	69.2 (45.9 to 92.5)	1.9 (1.7 to 2.2)
Any malignancy	846 (0.4)	57.5 (45.8 to 69.3)	3.4 (3.0 to 3.8)	307 (0.4)	175.6 (-80.2 to 431.5)	3.0 (2.5 to 3.4)
Blood loss anaemia	152 (0.1)	91.2 (44.9 to 137.5)	3.4 (2.7 to 4.0)	105 (0.2)	148.2 (24.8 to 271.6)	3.1 (2.4 to 3.8)
Cardiac arrhythmias	5588 (2.8)	111.6 (98.9 to 124.2)	3.5 (3.3 to 3.6)	1516 (2.1)	164.4 (111.4 to 217.3)	3.6 (3.3 to 3.8)
Cerebrovascular disease	1078 (0.5)	150.4 (109.3 to 191.5)	3.5 (3.2 to 3.8)	352 (0.5)	191.8 (103.1 to 280.5)	3.2 (2.7 to 3.6)
Chronic pulmonary disease	1676 (0.8)	90.6 (72.3 to 108.8)	3.3 (3.1 to 3.6)	442 (0.6)	98.4 (28.0 to 168.8)	3.3 (2.9 to 3.7)
Coagulopathy	1225 (0.6)	164.6 (128.4 to 200.8)	3.7 (3.4 to 4.1)	517 (0.7)	251.8 (135.0 to 368.6)	3.8 (3.3 to 4.2)
Congestive heart failure	1407 (0.7)	95.7 (79.6 to 111.7)	3.7 (3.5 to 3.9)	429 (0.6)	100.8 (49.8 to 151.8)	4.4 (3.9 to 4.9)
Deficiency anaemias	683 (0.3)	54.1 (34.8 to 73.4)	3.4 (2.9 to 3.8)	216 (0.3)	294.2 (-148.8 to 737.1)	3.1 (2.5 to 3.8)
Dementia	5694 (2.8)	65.2 (49.6 to 80.8)	2.8 (2.7 to 2.9)	1534 (2.1)	67.6 (31.5 to 103.8)	2.8 (2.6 to 3.0)
Depression	5713 (2.8)	56.5 (51.0 to 62.0)	2.6 (2.3 to 2.8)	1266 (1.8)	110.1 (52.3 to 168.0)	2.6 (2.3 to 3.0)
Diabetes with chronic complications	4466 (2.2)	105.0 (84.9 to 125.1)	3.4 (3.2 to 3.6)	1726 (2.4)	173.8 (99.6 to 248.0)	3.2 (3.0 to 3.5)
Diabetes without complications	10717 (5.3)	90.7 (76.9 to 104.4)	2.9 (2.8 to 3.0)	4349 (6.1)	132.9 (79.5 to 186.2)	2.7 (2.5 to 2.9)
Hemiplegia/paraplegia	962 (0.5)	194.9 (142.3 to 247.4)	3.5 (3.1 to 3.9)	338 (0.5)	146.4 (78.6 to 214.3)	3.6 (2.9 to 4.2)
Hypertension complicated	44 (0.0)	*	4.1 (2.7 to 5.4)	29 (0.0)	*	2.8 (2.0 to 3.7)
Hypertension uncomplicated	7057 (3.5)	113.0 (100.5 to 125.5)	3.4 (3.3 to 3.6)	2077 (2.9)	198.0 (138.2 to 257.8)	3.6 (3.4 to 3.8)
Hypothyroidism	312 (0.2)	139.0 (-0.6 to 278.6)	3.0 (2.4 to 3.6)	73 (0.1)	*	3.4 (2.1 to 4.7)
Metastatic solid tumor	477 (0.2)	68.3 (44.9 to 91.7)	3.6 (2.9 to 4.2)	157 (0.2)	230.4 (-247.6 to 708.4)	3.1 (2.5 to 3.7)
Mild liver disease	1351 (0.7)	113.4 (91.1 to 135.7)	3.3 (2.9 to 3.7)	550 (0.8)	91.7 (54.9 to 128.6)	3.1 (2.5 to 3.7)
Moderate or severe liver disease	159 (0.1)	168.4 (80.0 to 256.9)	3.5 (2.8 to 4.2)	55 (0.1)	114.4 (61.5 to 167.3)	4.1 (2.7 to 5.5)
Myocardial infarction	455 (0.2)	126.9 (59.2 to 194.7)	3.8 (3.3 to 4.4)	126 (0.2)	*	4.1 (3.2 to 4.9)
Obesity	501 (0.3)	160.7 (101.2 to 220.2)	3.9 (3.2 to 4.5)	140 (0.2)	295.8 (-25.0 to 616.5)	4.4 (3.1 to 5.7)
Peptic ulcer disease	105 (0.1)	90.4 (48.1 to 132.8)	4.1 (2.9 to 5.2)	55 (0.1)	65.2 (16.5 to 113.9)	4.2 (2.3 to 6.0)

Peripheral vascular disease	447 (0.2)	207.7 (100.4 to 314.9)	3.7 (3.1 to 4.2)	391 (0.5)	85.4 (31.1 to 139.6)	3.1 (2.6 to 3.6)
Psychoses	937 (0.5)	88.6 (67.3 to 110.0)	2.8 (2.4 to 3.3)	182 (0.3)	106.9 (47.5 to 166.4)	3.6 (2.1 to 5.0)
Pulmonary circulation disorders	349 (0.2)	123.5 (84.3 to 162.7)	3.7 (3.3 to 4.2)	91 (0.1)	358.2 (-66.9 to 783.3)	4.3 (3.0 to 5.6)
Renal disease including renal failure	3457 (1.7)	98.0 (76.8 to 119.1)	3.6 (3.5 to 3.8)	1095 (1.5)	163.1 (80.6 to 245.6)	3.4 (3.1 to 3.8)
Rheumatic disease including some other connective tissue disorders	307 (0.2)	96.4 (38.3 to 154.4)	2.9 (2.4 to 3.3)	107 (0.2)	0.0 (0.0 to 0.0)	3.8 (2.8 to 4.8)
Valvular disease	551 (0.3)	112.4 (75.9 to 149.0)	3.6 (3.2 to 4.0)	159 (0.2)	185.8 (-28.4 to 400.0)	4.3 (3.5 to 5.1)

Notes:
*Cell count 1-4 suppressed to protect confidentiality
1. n=6696
2. n=713

Table A7: Performance of selected model fitting strategies in assessing the effect of comorbidity on selected outcome measures (NSW and WA)

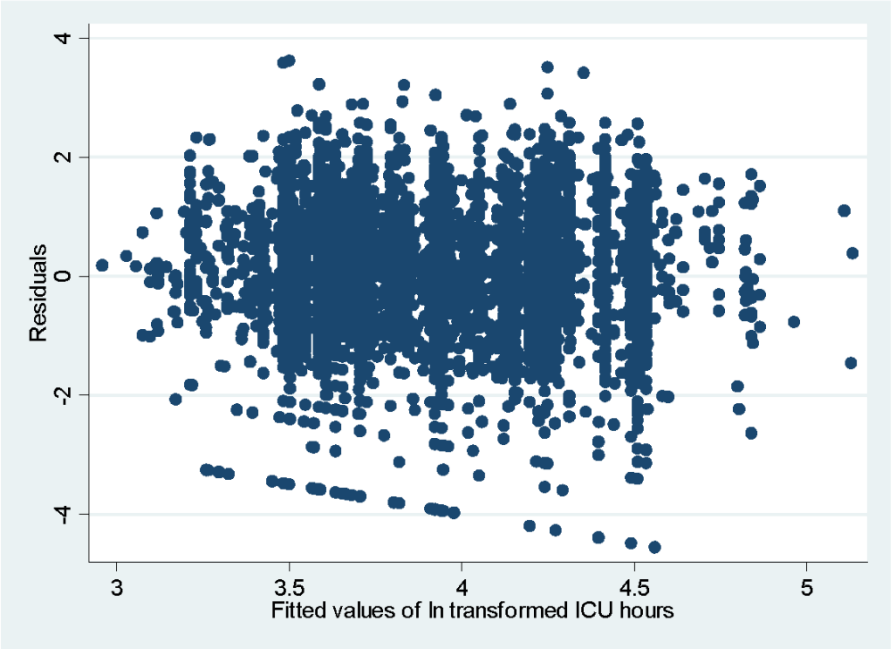
Models	Ln (ICU hours)		Number of complications	
	Adjusted R^2	Model fit AIC	McFadden's Adjusted R^2	Model fit AIC
NSW				
(i) Baseline model[1,2]	0.065	22058	0.019	64933
(ii) Baseline model + individual comorbidity (selected) (binary representation)	0.070	22021	0.023	64619
(iii) Baseline model + comorbidity using ICI (integer value of actual weight)	0.069	22025	0.020	64847
(iv) Baseline model + comorbidity using CCI weights	0.066	22048	0.021	64746
(v) Baseline model + comorbidity using Quan weights	0.067	22042	0.020	64818
(vi) Baseline model + ECM	0.082	21962	0.024	64575
WA				
(i) Baseline model[1,2]	0.189	2209	0.029	29387
(ii) Baseline model + individual comorbidity (selected) (binary representation)	0.230	2177	0.037	29148
(iii) Baseline model + comorbidity using ICI (integer value of actual weight)	0.225	2178	0.032	29296
(iv) Baseline model + comorbidity using CCI weights	0.200	2200	0.032	29317
(v) Baseline model + comorbidity using Quan weights	0.194	2206	0.031	29329
(vi) Baseline model + ECM	0.238	2193	0.038	29125

Notes:
1. Baseline model includes age, sex, injury severity, injury type and body region; outcome =ICU stay hours (Ln transformed linear model)
2. Baseline model includes age, sex, injury type, injury severity and body region; outcome=number of complications for those with at least one complication (negative binomial model)
note: See Table A3 for selected comorbidities for each outcome

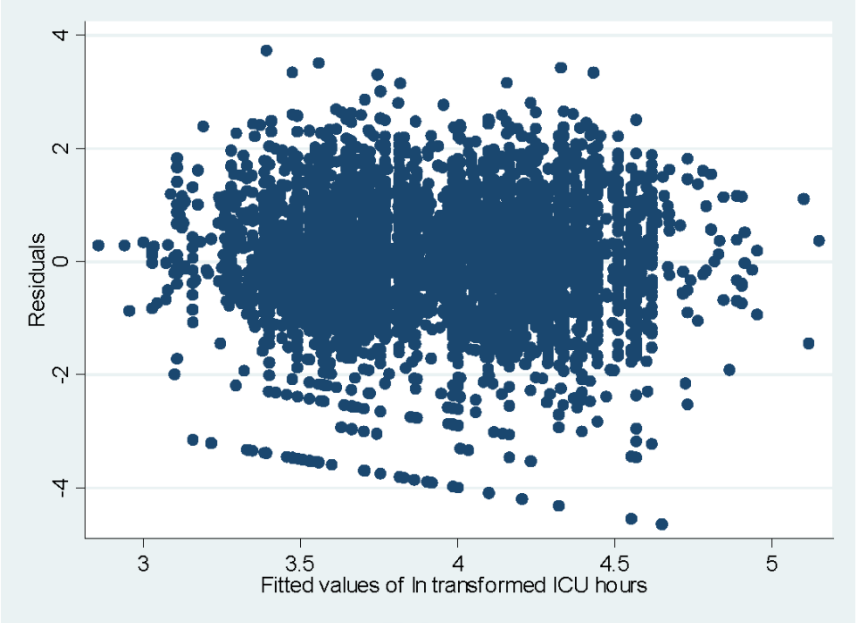
Appendix A1: Residual plots

ICU hours

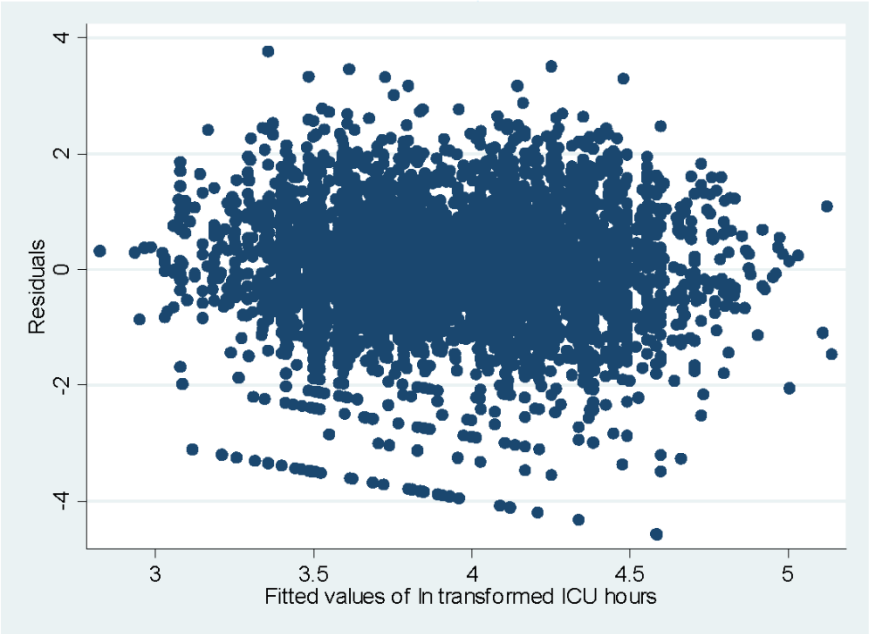
Baseline model (age, sex, body region, injury type, injury severity geographic region)



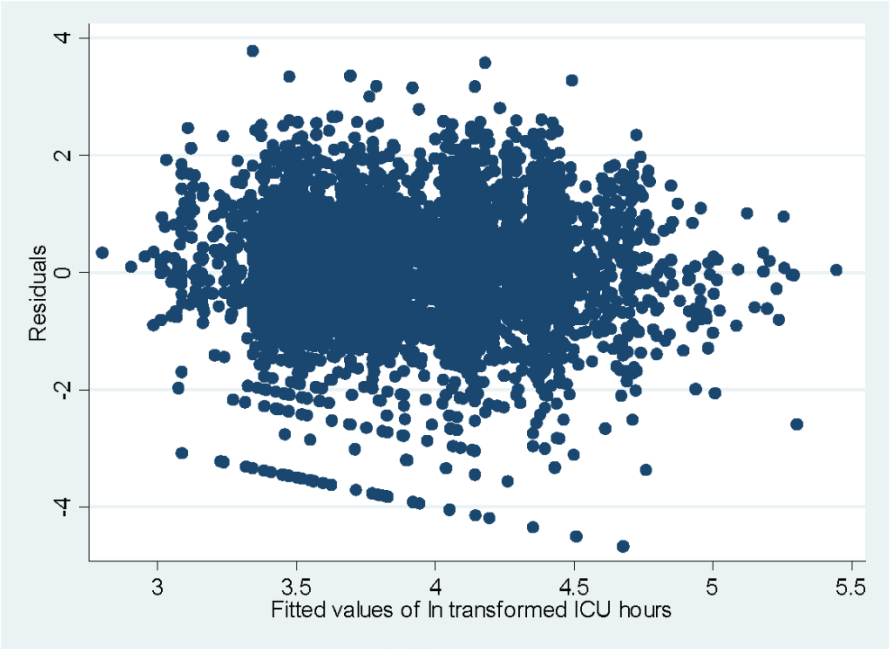
Baseline + one comorbidity



Baseline + count of comorbidities

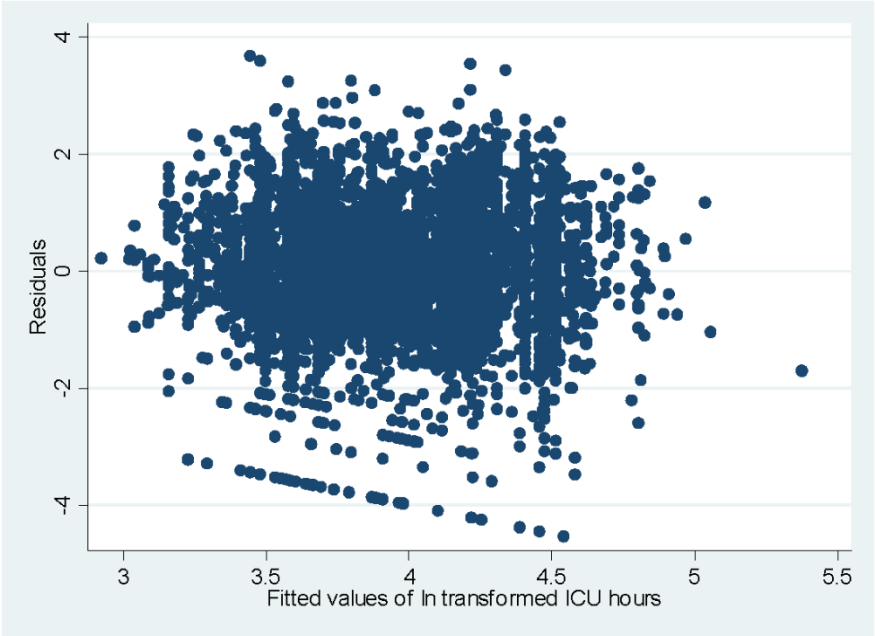


Baseline + presence of all 31 comorbidities

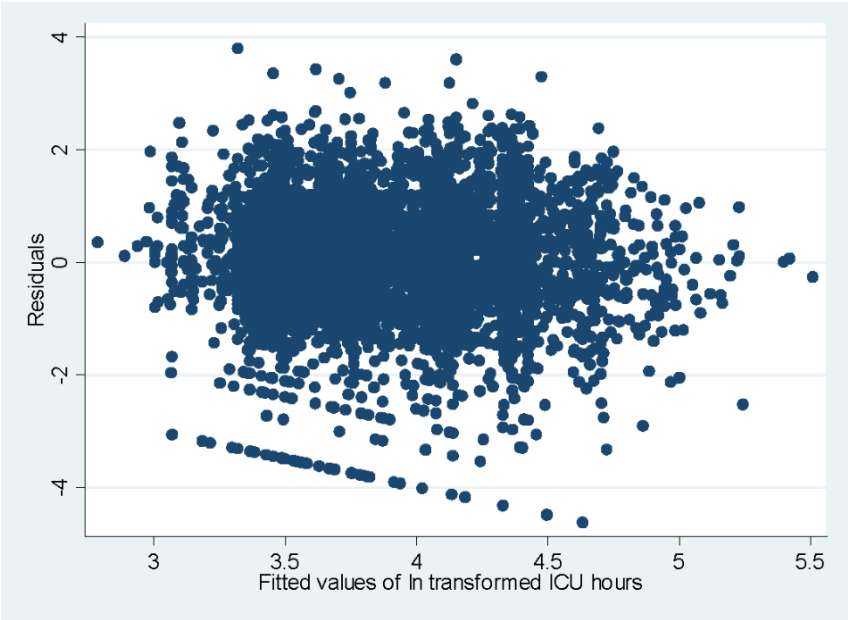


Baseline + Charlson Comorbidity Index (CCI)

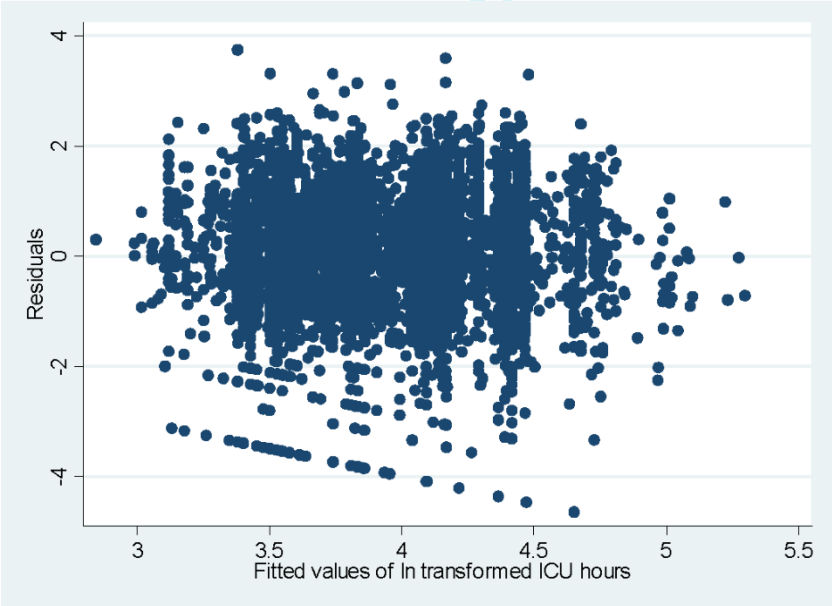
Baseline + updated CCI



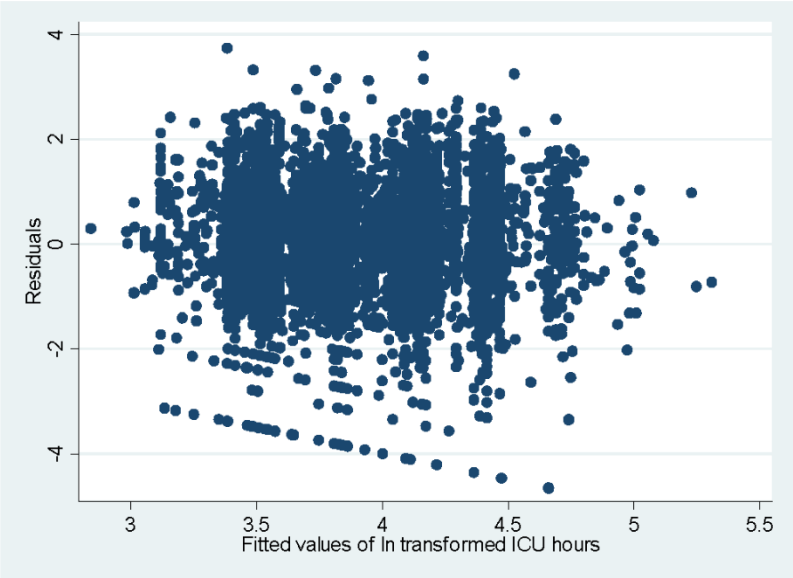
Baseline + Elixhauser Comorbidity Measure



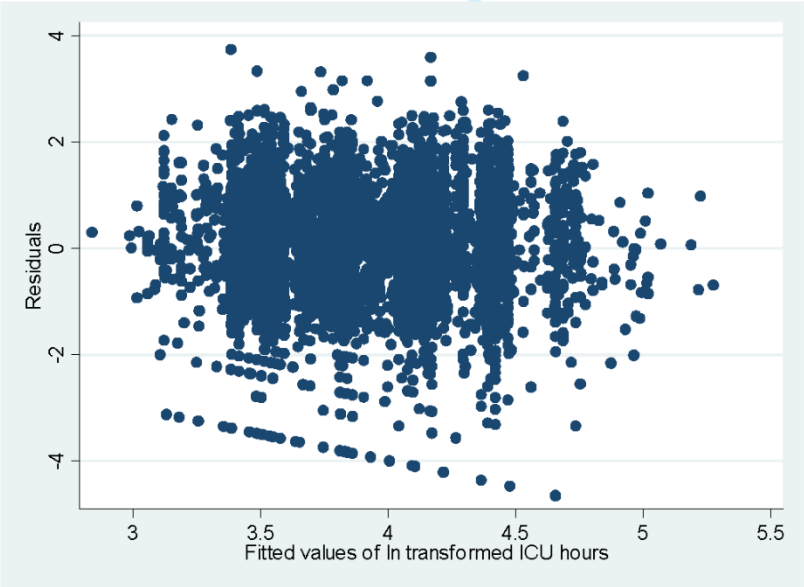
Baseline + AICI-icu with binary representation of 5 comorbidities



Baseline + AICI-icu with actual weights (5 conditions)

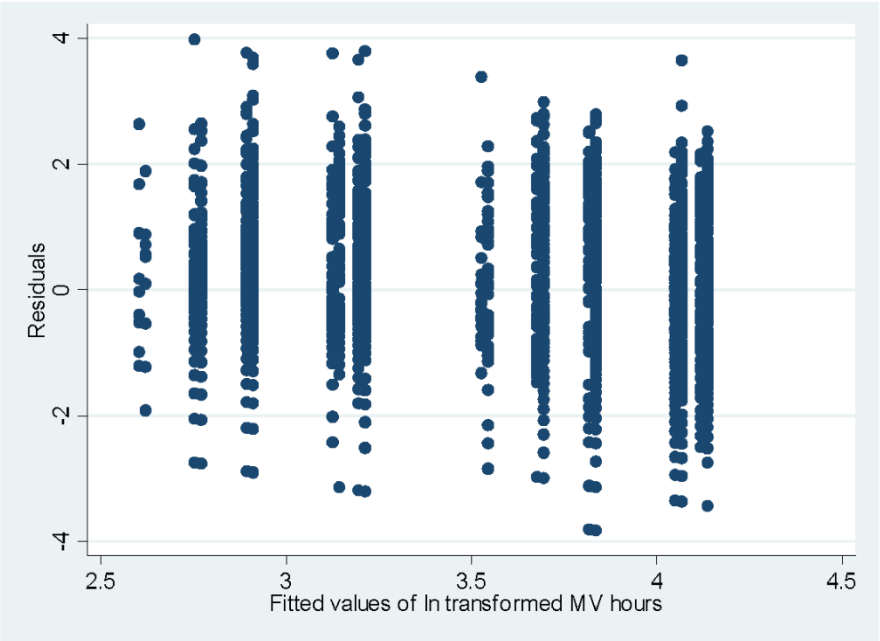


Baseline + AICI-icu with rounded weights (5 conditions)

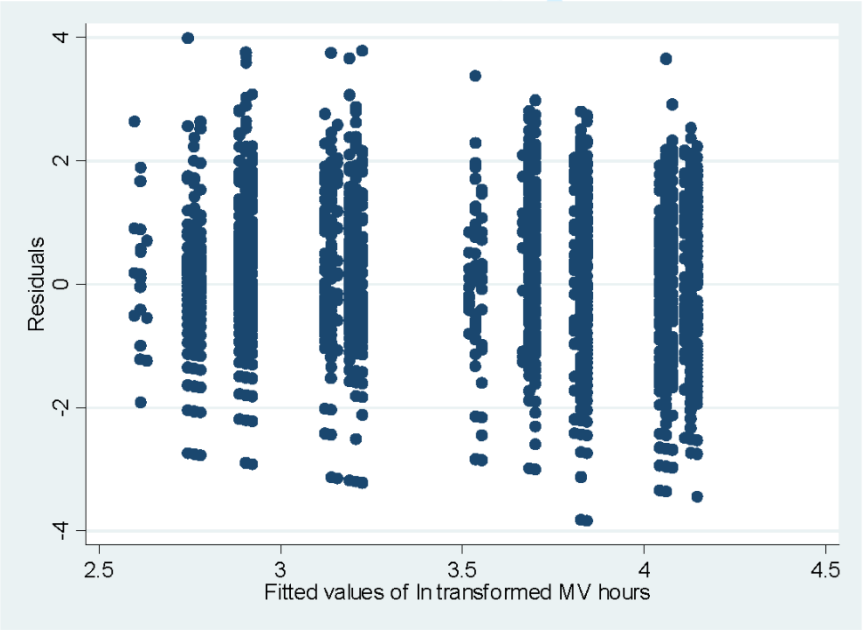


MV hours

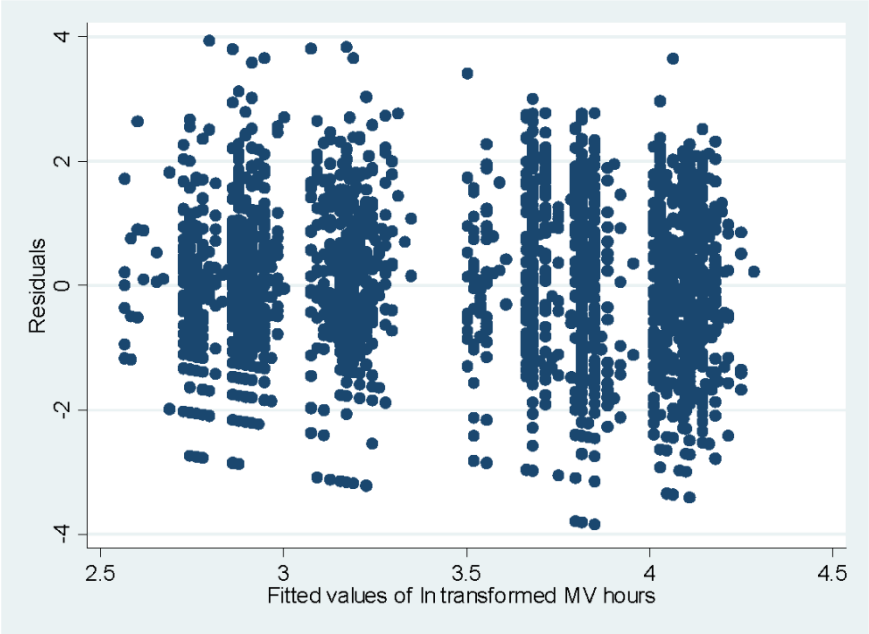
Baseline (age, sex and injury severity)



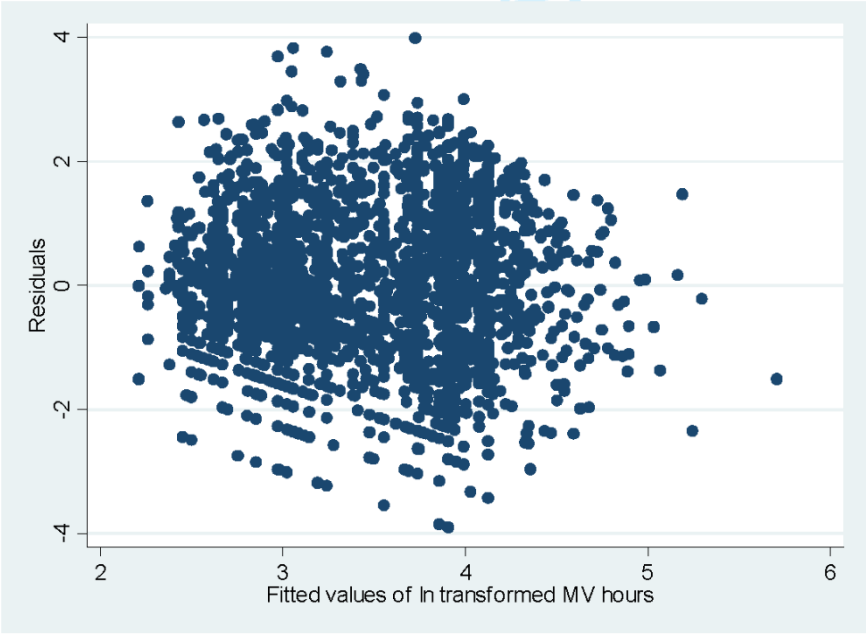
Baseline + at least one comorbidity



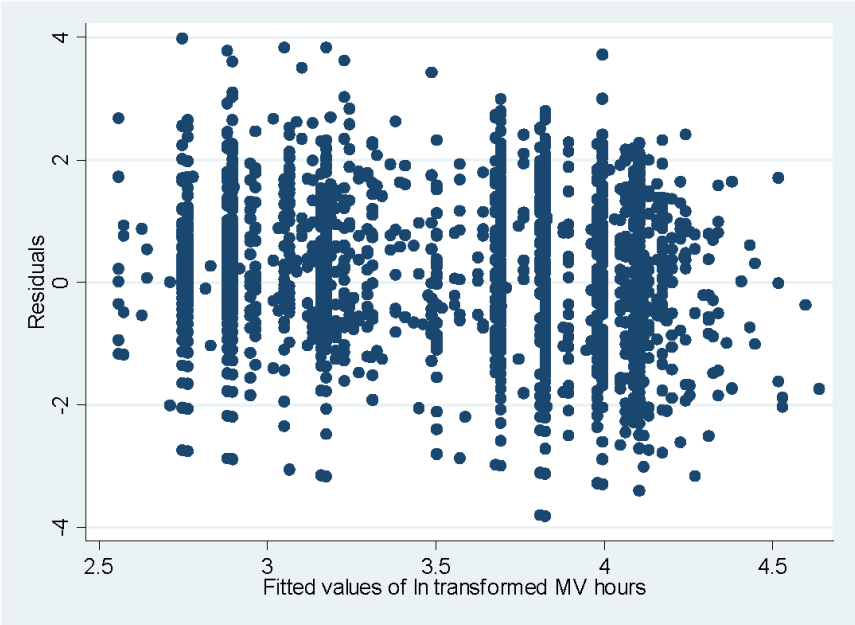
Baseline + count of comorbidities



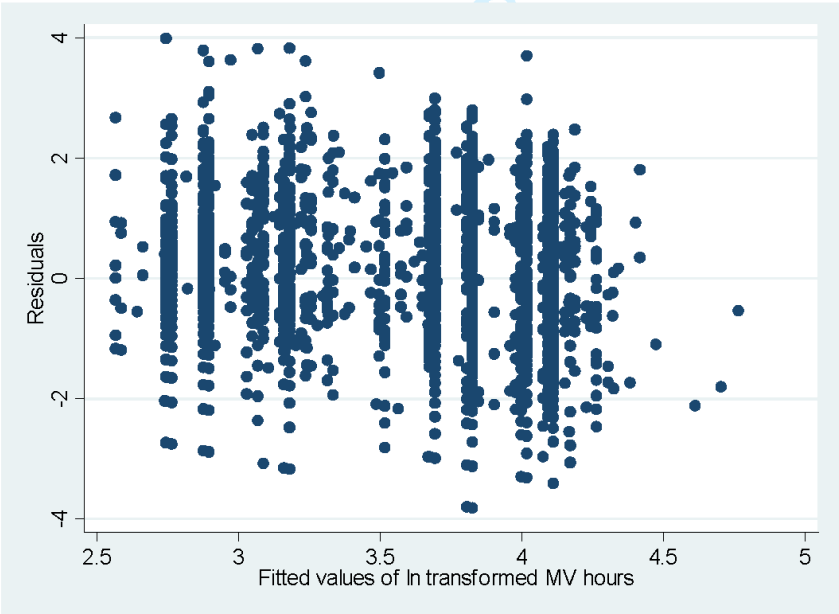
Baseline + all 31 comorbidities



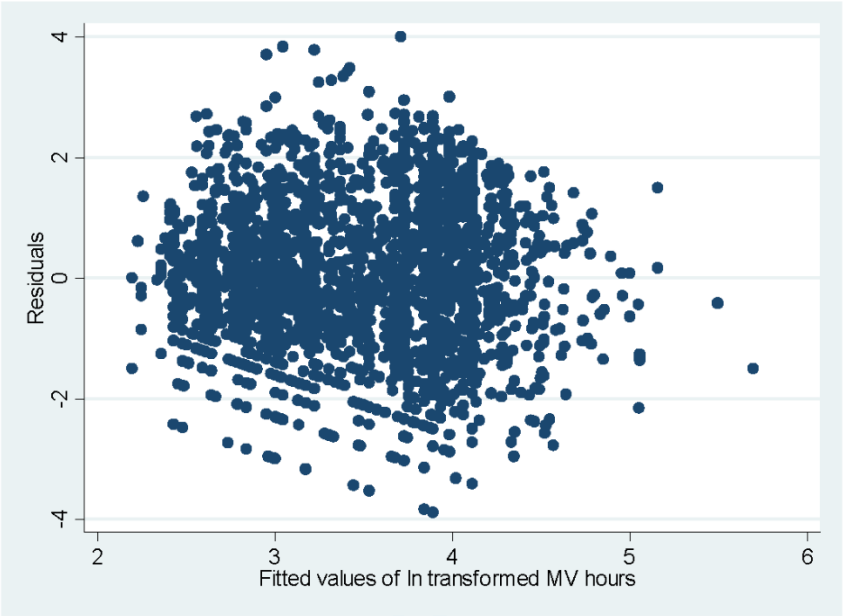
Baseline + CCI



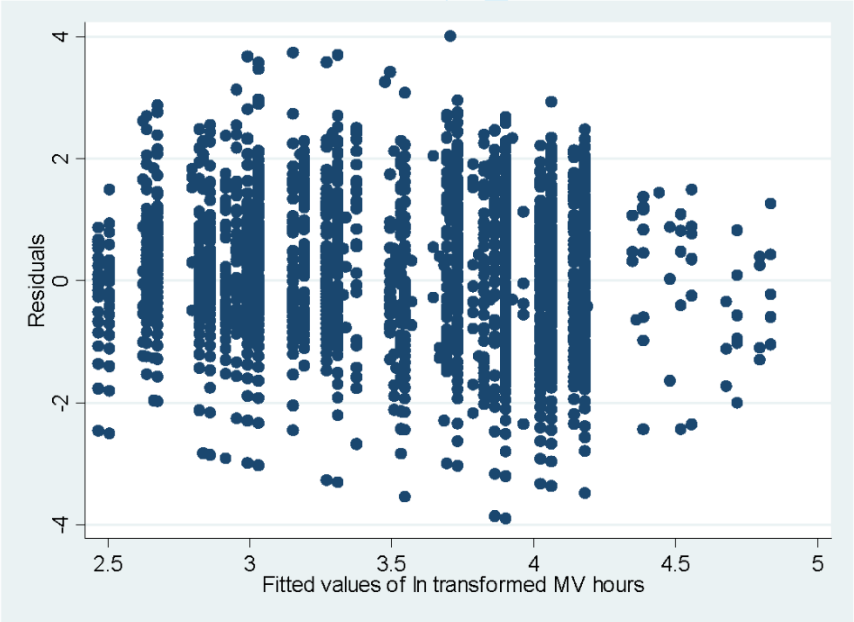
Baseline + updated CCI



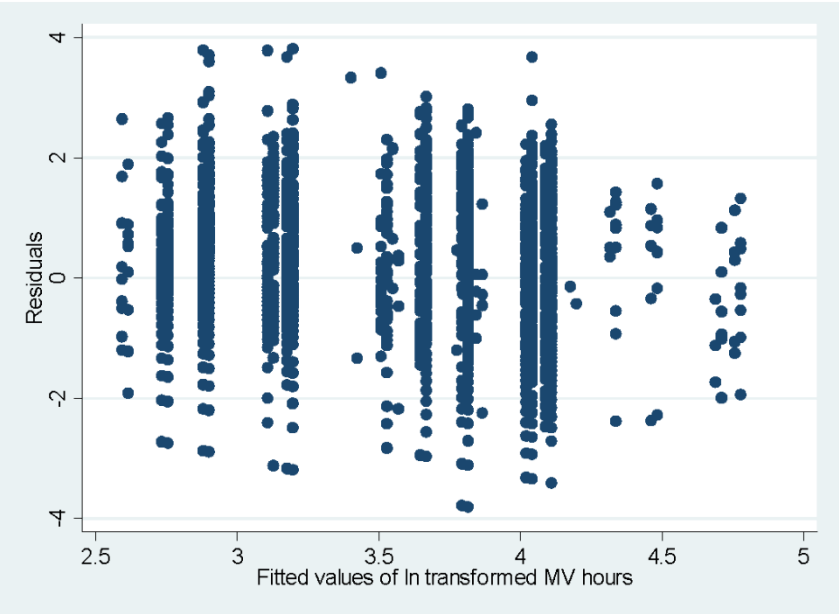
Baseline + ECM



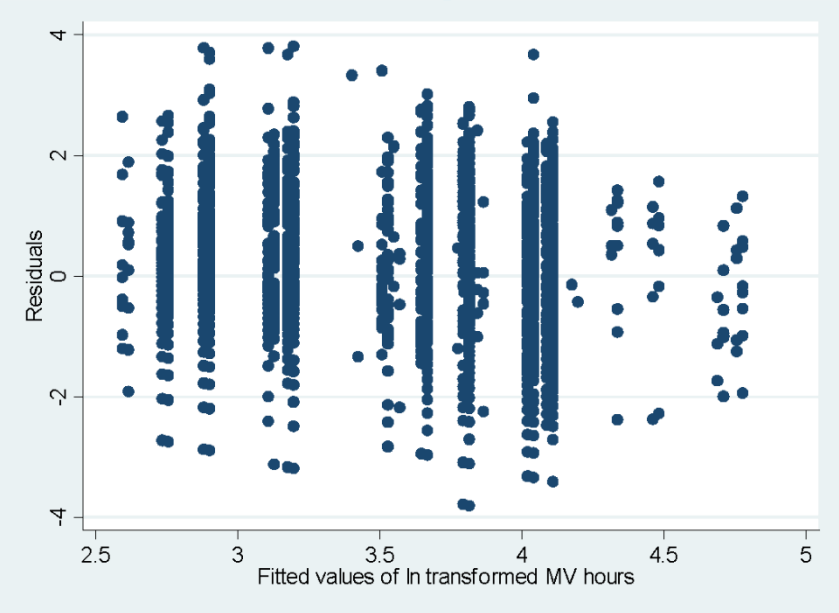
Baseline + AICI-mv with binary representation of 2 comorbidities



Baseline + AICI-mv with actual weights (1 condition)

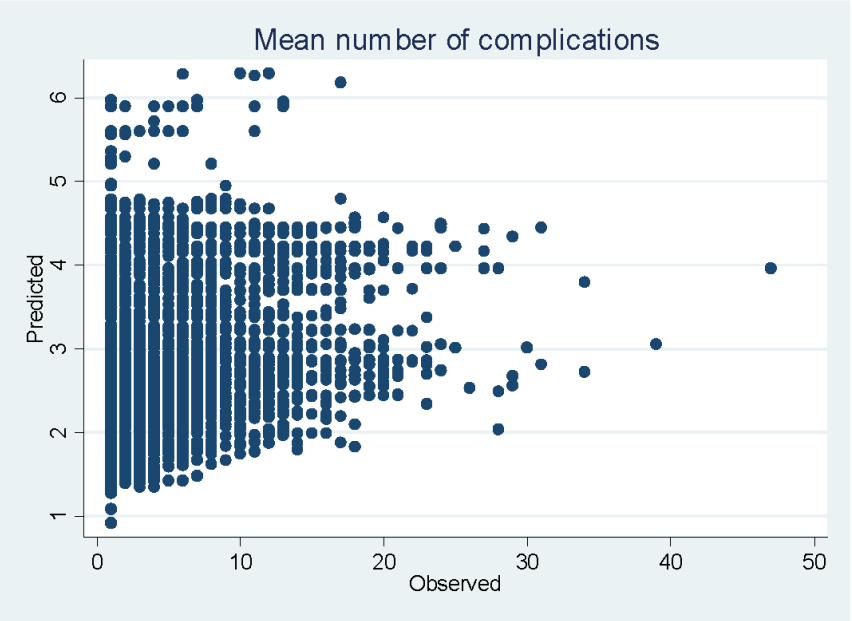


Baseline + AICI-mv with rounded weights (1 condition)

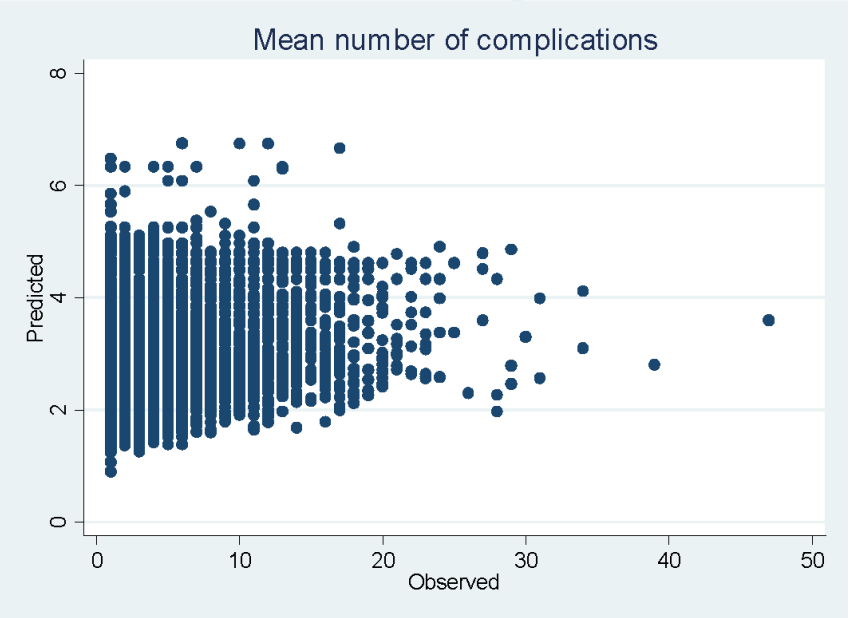


Complications

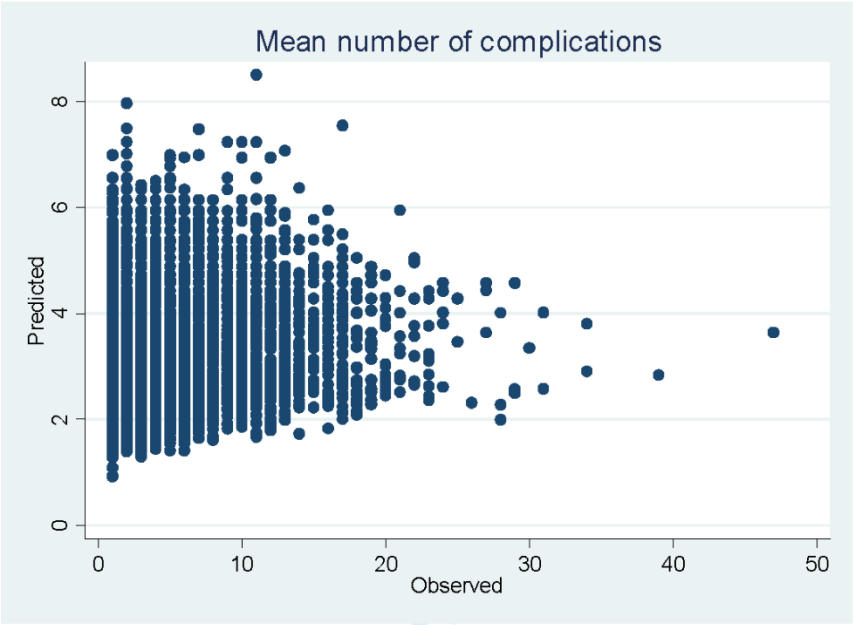
Baseline model (age, sex, body region, injury type and injury severity)



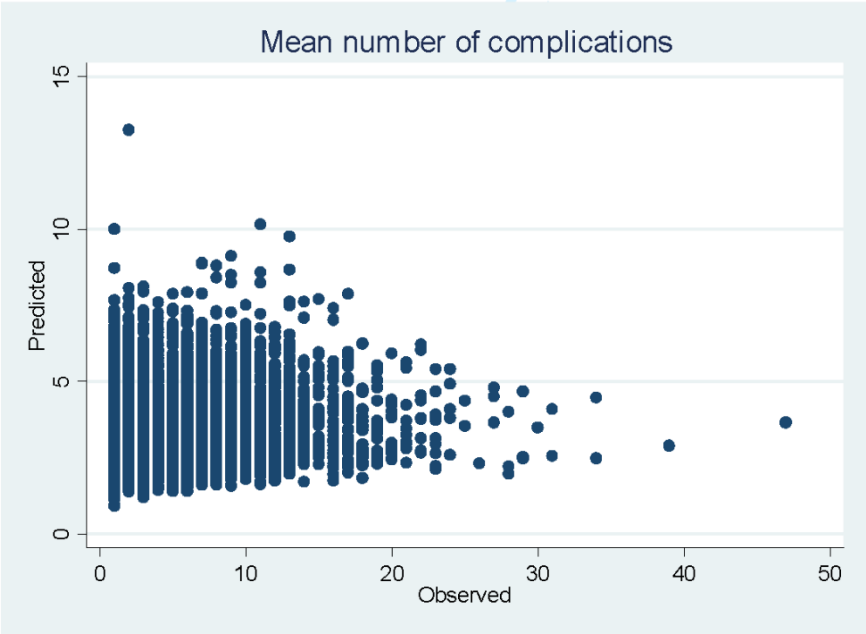
Baseline + one comorbidity



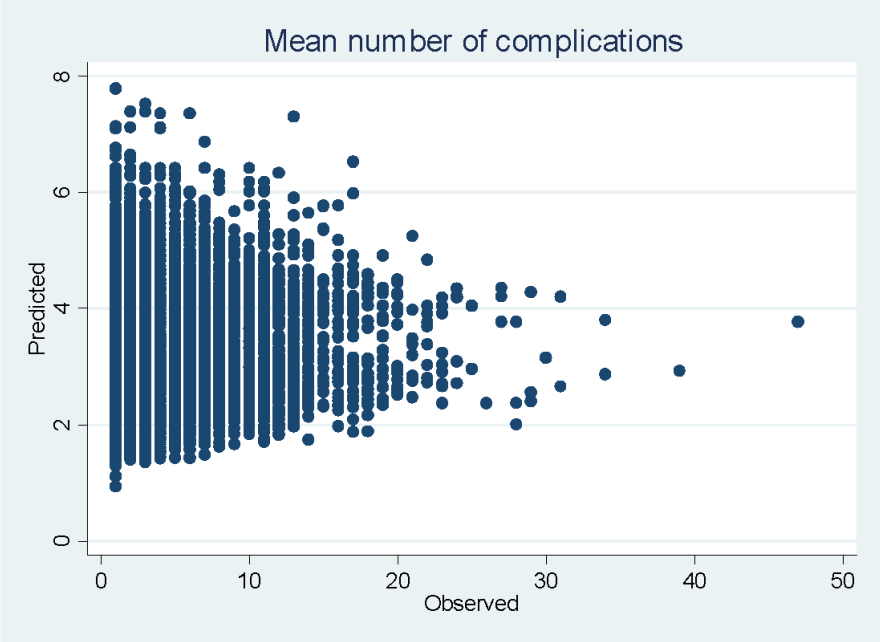
Baseline + count of comorbidities



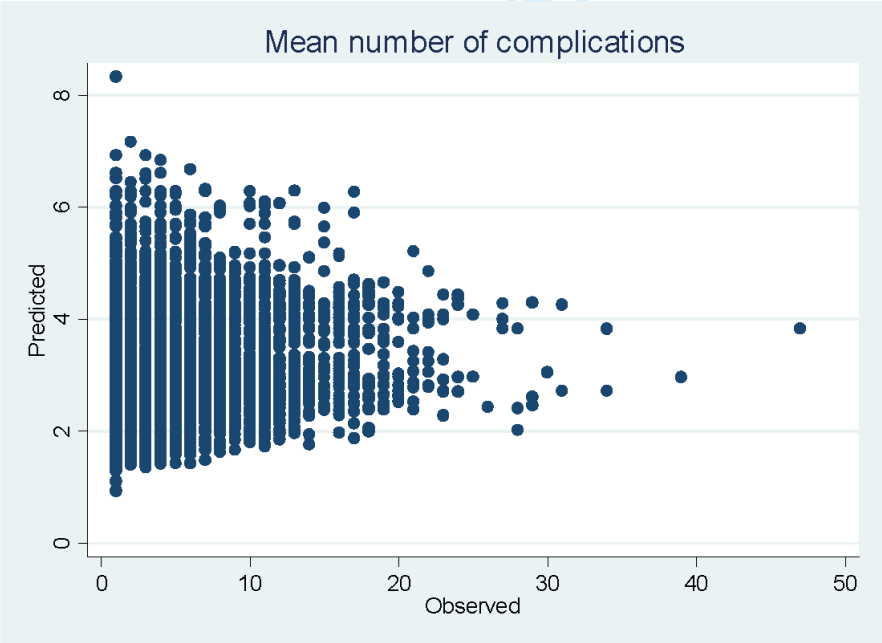
Baseline + presence of all 31 comorbidities



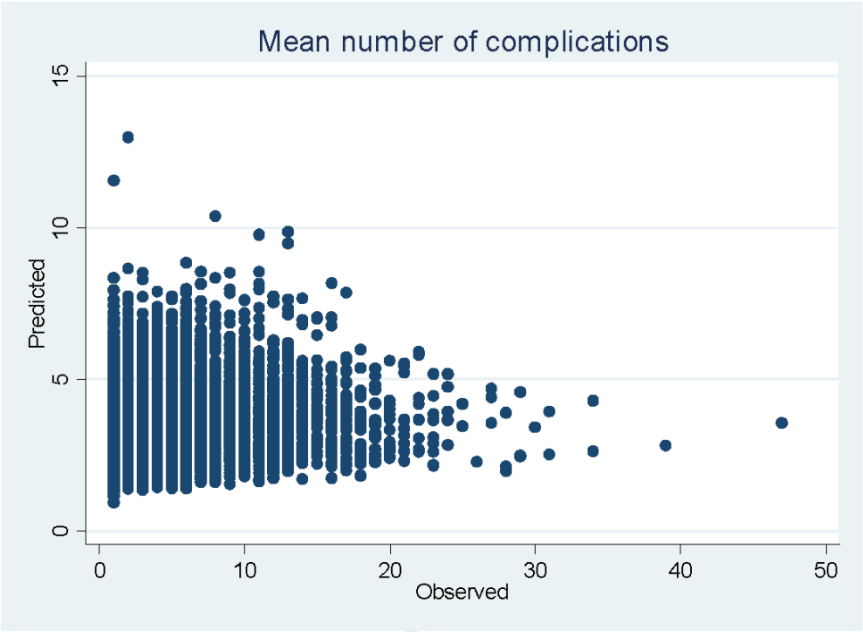
Baseline + Charlson Comorbidity Index (CCI)



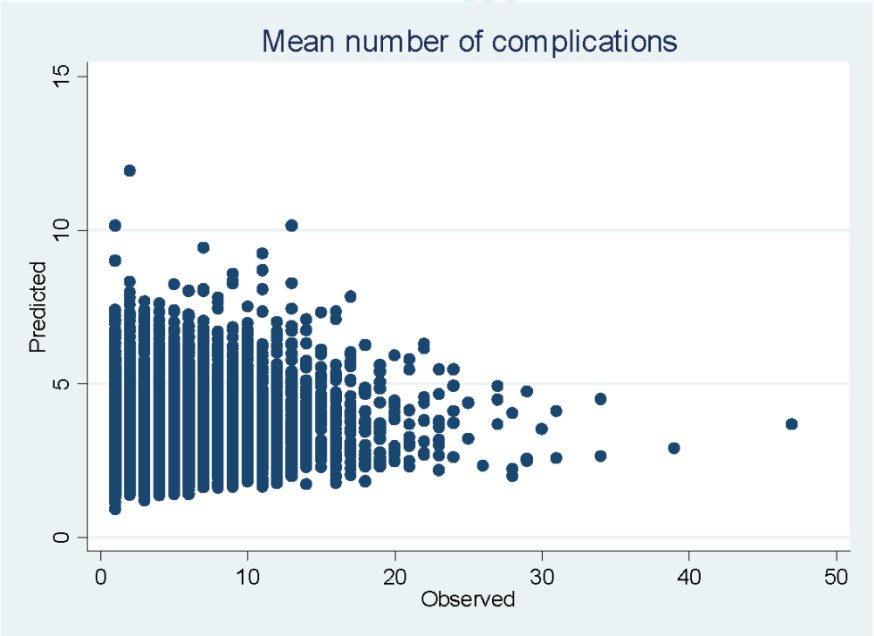
Baseline + updated CCI



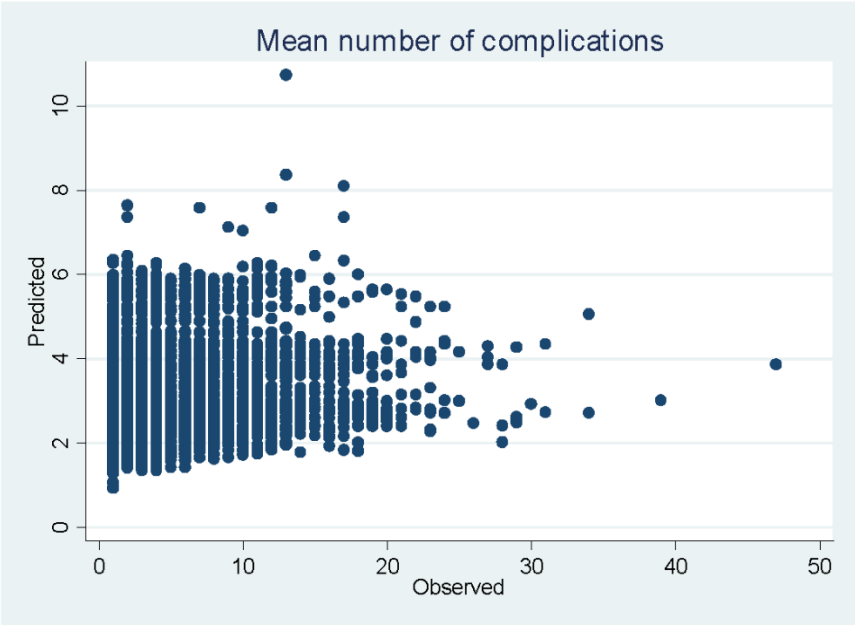
Baseline + Elixhauser Comorbidity Measure



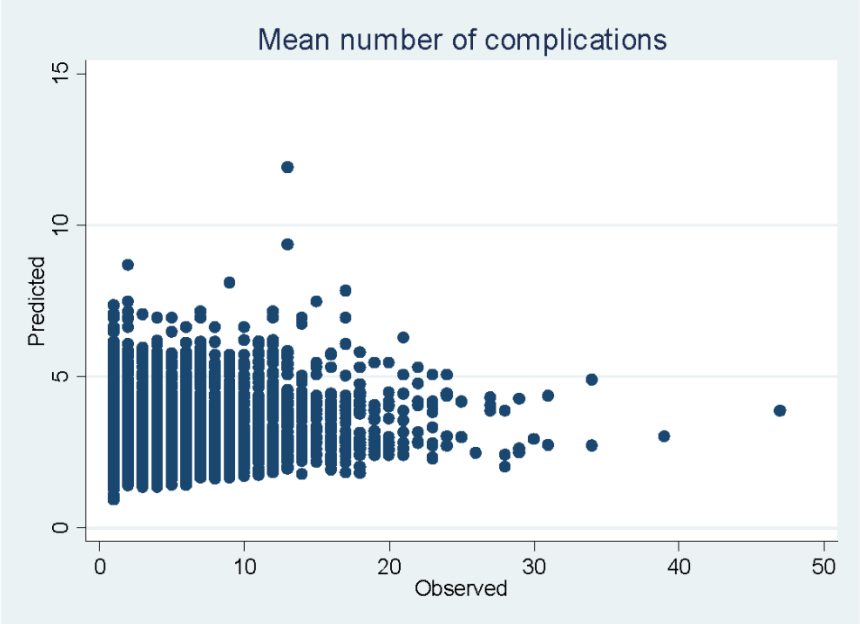
Baseline + AICI-comp with binary representation of 15 comorbidities



Baseline + AICI-comp with actual weights (5 conditions)

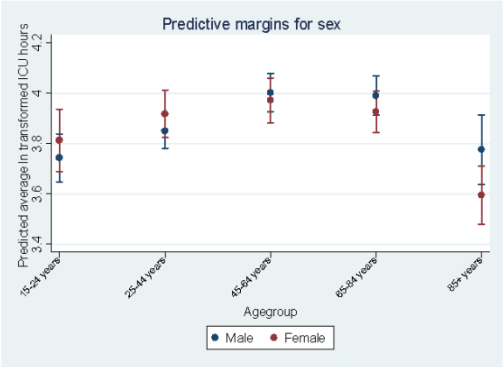


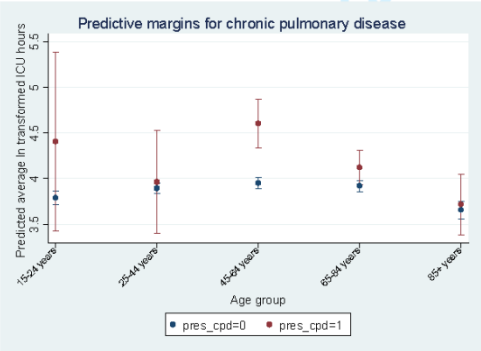
Baseline + AICI-comp with rounded weights (5 conditions)

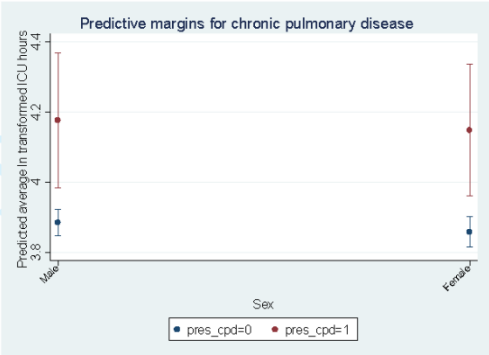


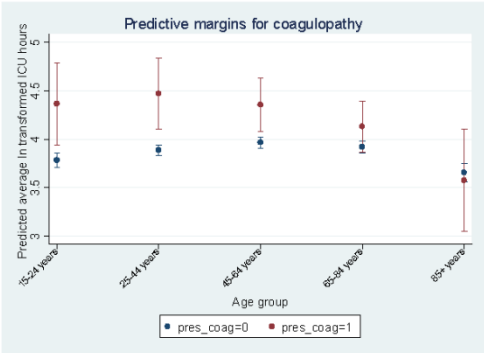
Appendix A2 – Interaction plots

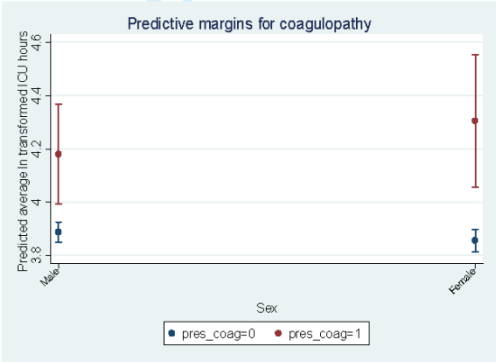
ICU hours

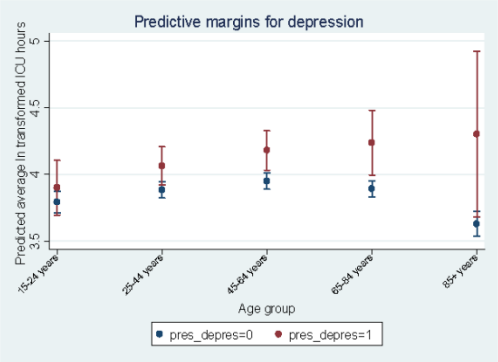


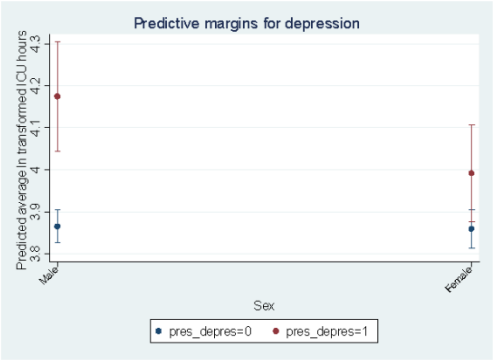


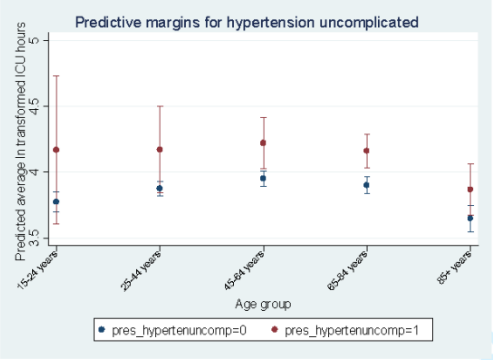


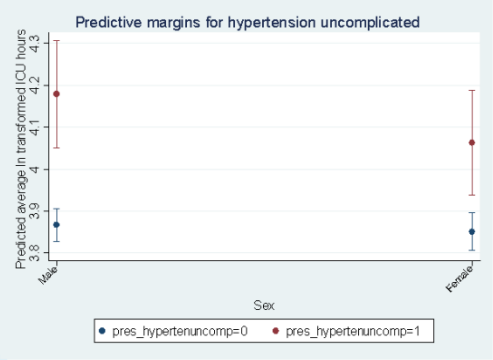


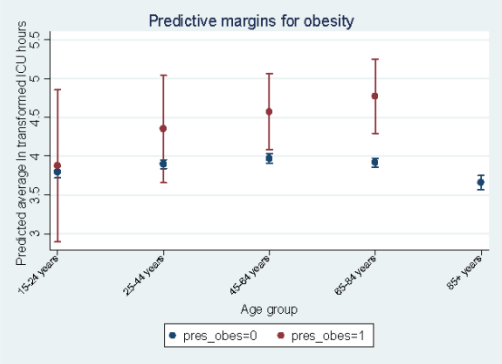



Predictive margins for depression
Predicted average ln transformed ICU hours
3.5
4
4.5
5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_depres=0
pres_depres=1


Predictive margins for depression
Predicted average ln transformed ICU hours
3.8
3.9
4
4.1
4.2
4.3
Male
Female
Sex
pres_depres=0
pres_depres=1

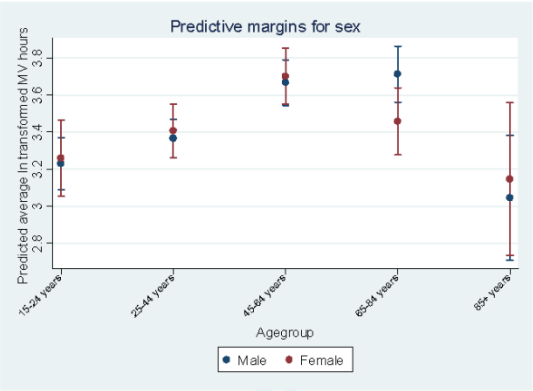

Predictive margins for hypertension uncomplicated
Predicted average ln transformed ICU hours
3.5
4
4.5
5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_hypertenuncomp=0
pres_hypertenuncomp=1

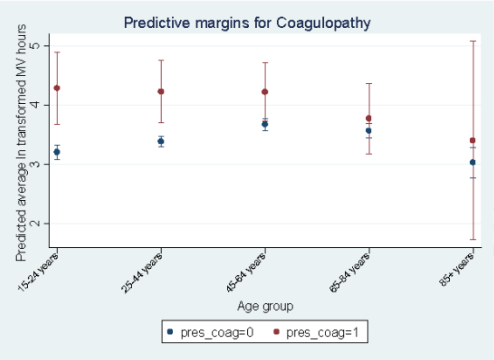

Predictive margins for hypertension uncomplicated
Predicted average ln transformed ICU hours
3.8
3.9
4
4.1
4.2
4.3
Male
Female
Sex
pres_hypertenuncomp=0
pres_hypertenuncomp=1

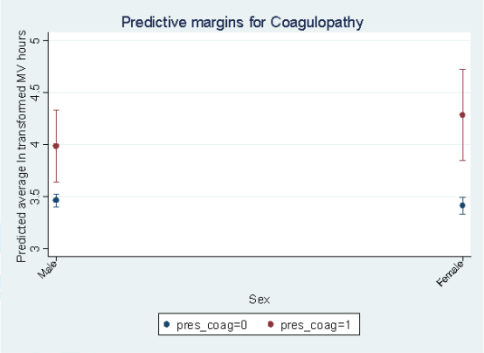

Predictive margins for obesity
Predicted average ln transformed ICU hours
3
3.5
4
4.5
5
5.5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_obes=0
pres_obes=1

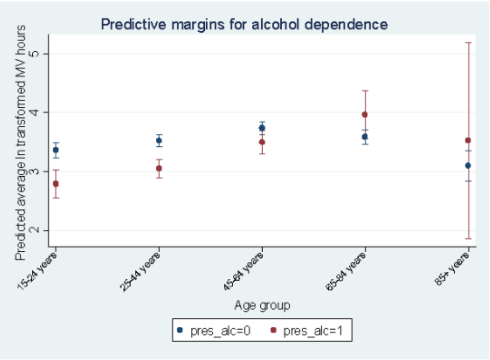

Predictive margins for obesity
Predicted average ln transformed ICU hours
3.5
4
4.5
5
Male
Female
Sex
pres_obes=0
pres_obes=1

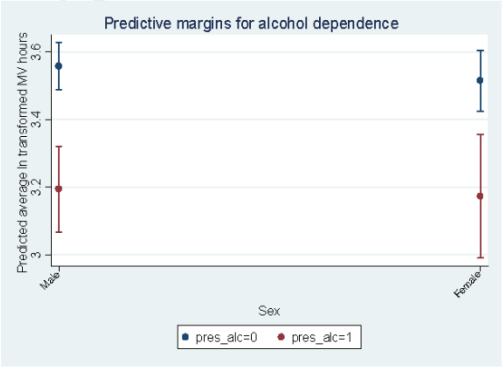
MV hours


Predictive margins for sex
Predicted average ln transformed MV hours
2.8
3
3.2
3.4
3.6
3.8
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Agegroup
Male
Female

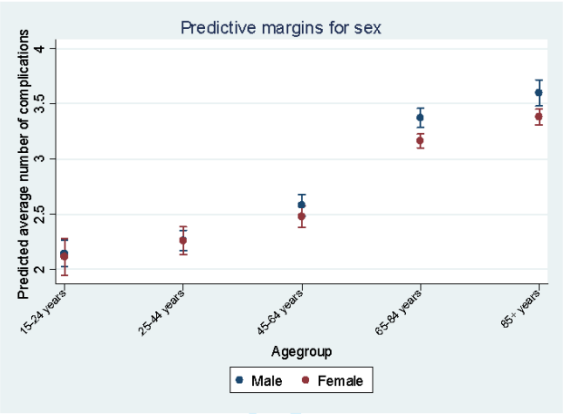

Predictive margins for Coagulopathy
Predicted average ln transformed MV hours
2
3
4
5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

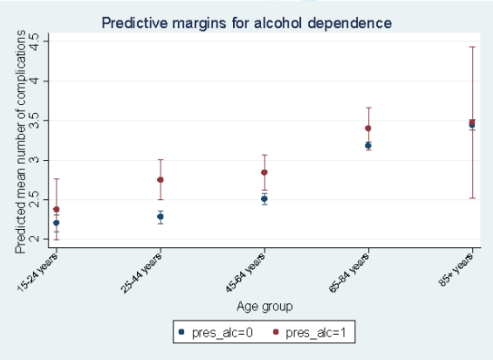

Predictive margins for Coagulopathy
Predicted average ln transformed MV hours
3
3.5
4
4.5
5
Male
Female
Sex
pres_coag=0
pres_coag=1

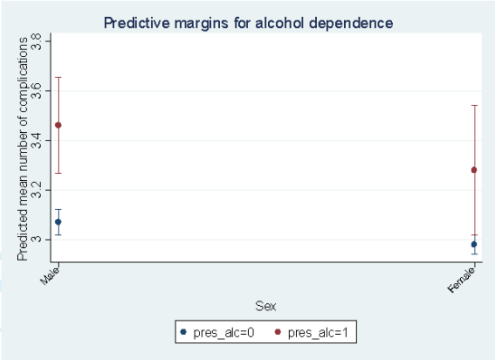

Predictive margins for alcohol dependence
Predicted average ln transformed MV hours
2
3
4
5
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_alc=0
pres_alc=1

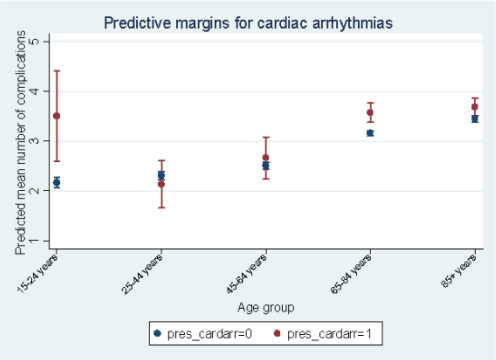

Predictive margins for alcohol dependence
Predicted average ln transformed MV hours
3
3.2
3.4
3.6
Male
Female
Sex
pres_alc=0
pres_alc=1

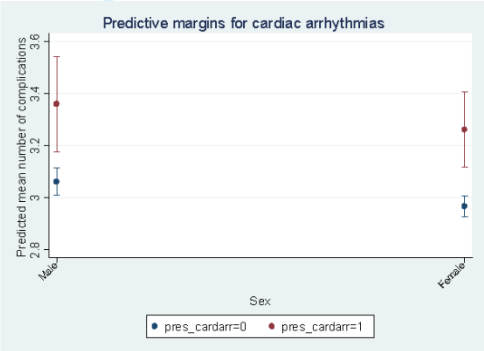
Complications

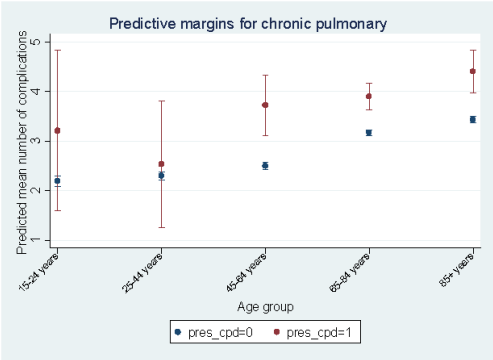


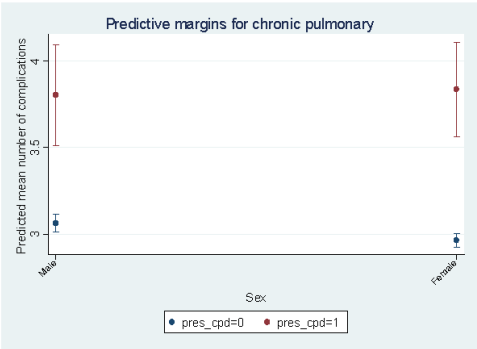


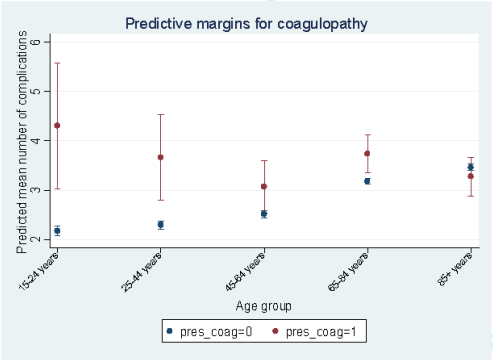


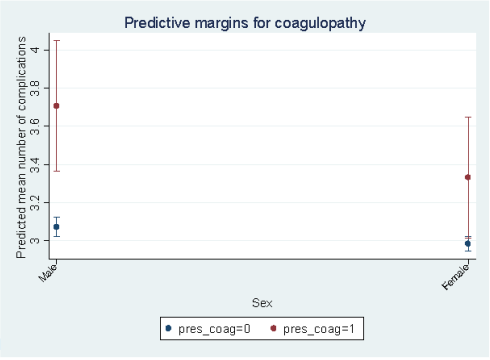


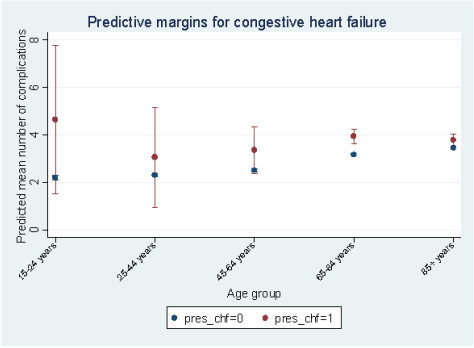


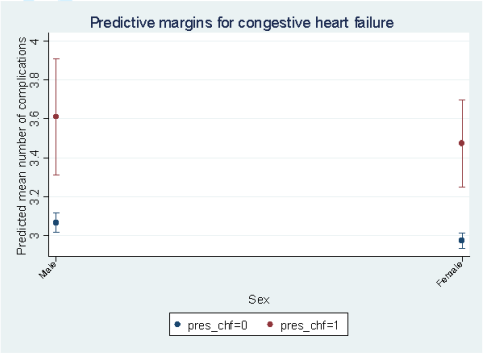

Predictive margins for chronic pulmonary
Predicted mean number of complications
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_cpd=0
pres_cpd=1

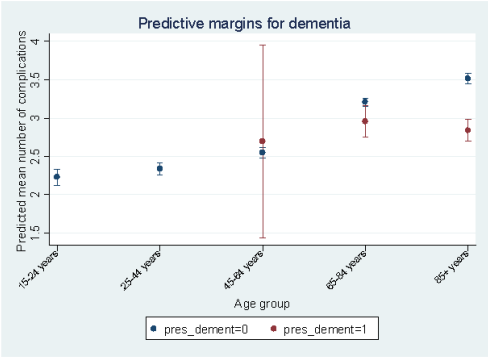

Predictive margins for chronic pulmonary
Predicted mean number of complications
Male
Female
Sex
pres_cpd=0
pres_cpd=1

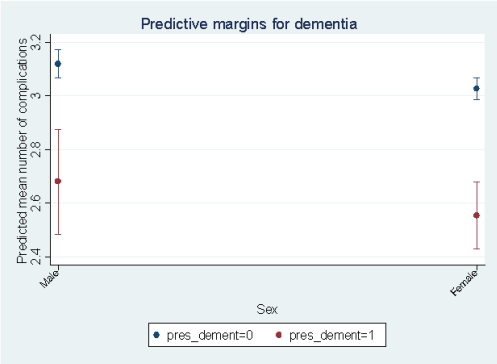

Predictive margins for coagulopathy
Predicted mean number of complications
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_coag=0
pres_coag=1

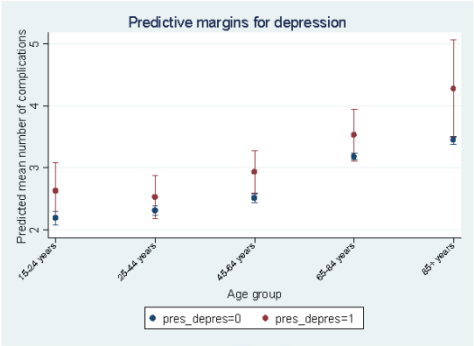

Predictive margins for coagulopathy
Predicted mean number of complications
Male
Female
Sex
pres_coag=0
pres_coag=1

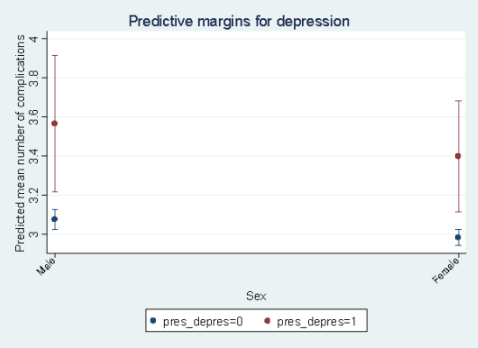

Predictive margins for congestive heart failure
Predicted mean number of complications
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_chf=0
pres_chf=1

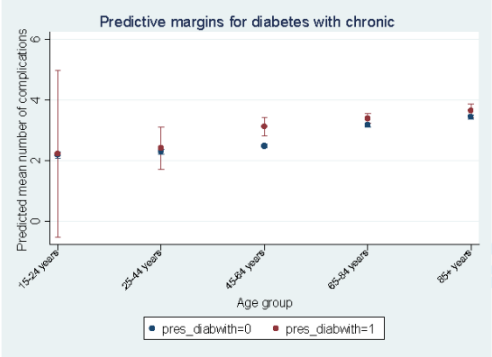

Predictive margins for congestive heart failure
Predicted mean number of complications
Male
Female
Sex
pres_chf=0
pres_chf=1

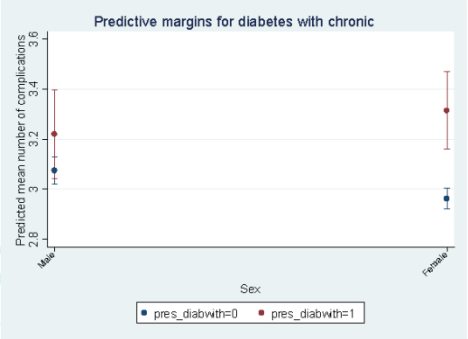

Predictive margins for dementia
Predicted mean number of complications
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
Age group
pres_dement=0
pres_dement=1

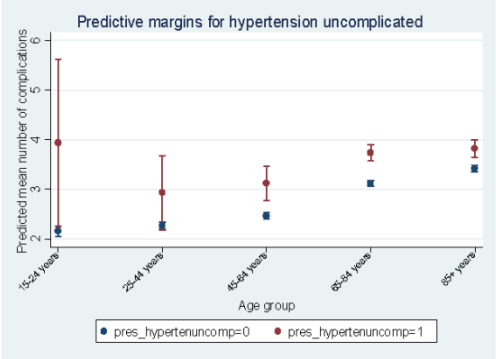

Predictive margins for dementia
Predicted mean number of complications
Male
Female
Sex
pres_dement=0
pres_dement=1

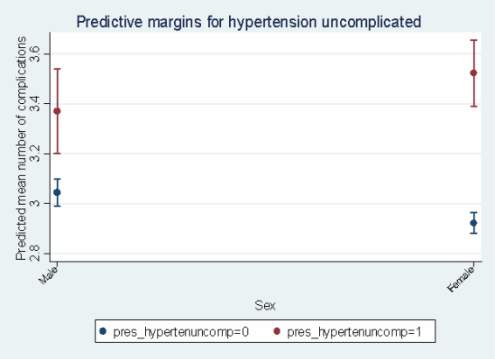

Predictive margins for depression
Predicted mean number of complications
Age group
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
pres_depres=0
pres_depres=1

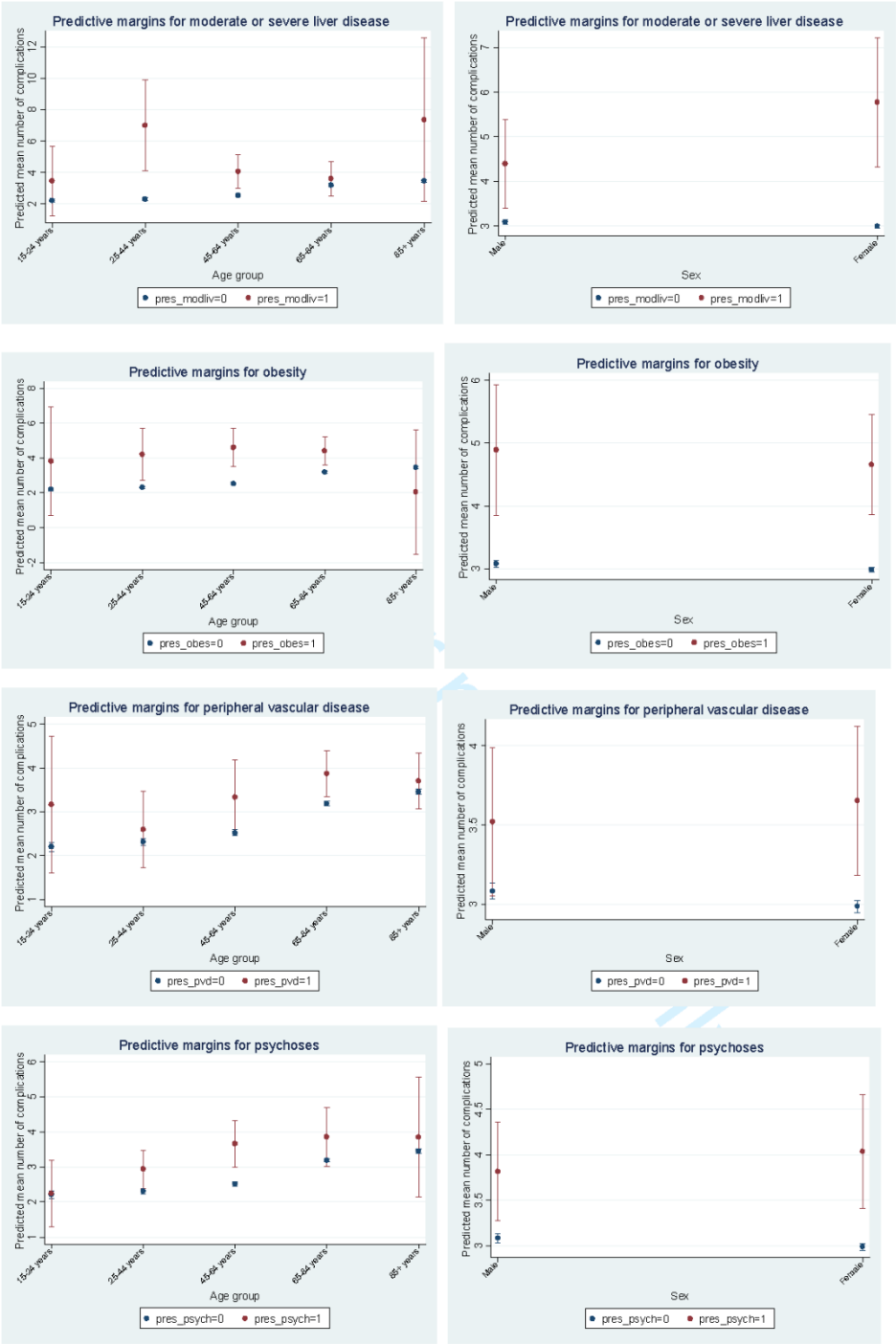

Predictive margins for depression
Predicted mean number of complications
Sex
Male
Female
pres_depres=0
pres_depres=1

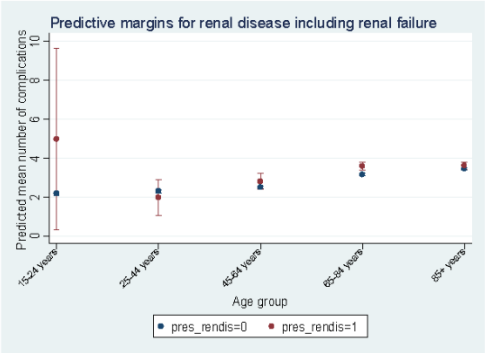

Predictive margins for diabetes with chronic
Predicted mean number of complications
Age group
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
pres_diabwith=0
pres_diabwith=1

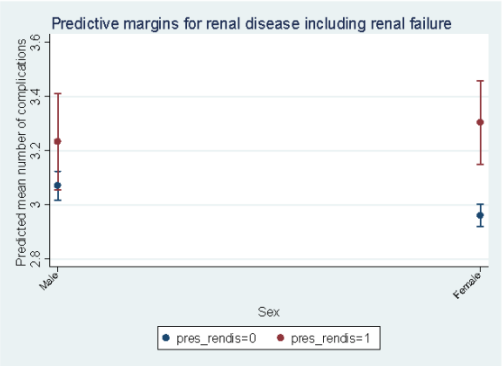

Predictive margins for diabetes with chronic
Predicted mean number of complications
Sex
Male
Female
pres_diabwith=0
pres_diabwith=1

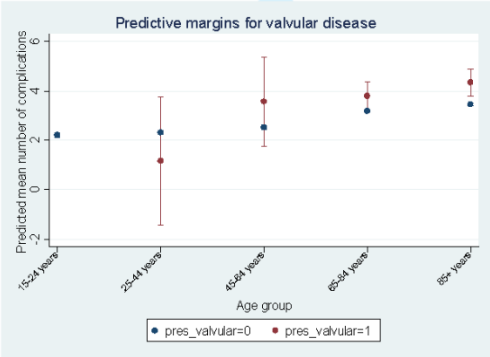

Predictive margins for hypertension uncomplicated
Predicted mean number of complications
Age group
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
pres_hypertenuncomp=0
pres_hypertenuncomp=1

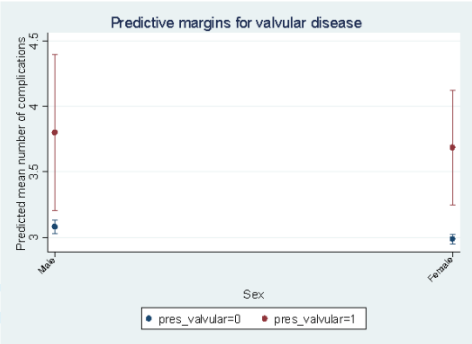

Predictive margins for hypertension uncomplicated
Predicted mean number of complications
Sex
Male
Female
pres_hypertenuncomp=0
pres_hypertenuncomp=1


Predictive margins for moderate or severe liver disease
Predicted mean number of complications
Age group
15-24 years
25-44 years
45-64 years
65-84 years
85+ years
pres_modliv=0
pres_modliv=1
Predictive margins for moderate or severe liver disease
Predicted mean number of complications
Sex
Male
Female
pres_modliv=0
pres_modliv=1
Predictive margins for obesity
Predicted mean number of complications
Age group
pres_obes=0
pres_obes=1
Predictive margins for obesity
Predicted mean number of complications
Sex
pres_obes=0
pres_obes=1
Predictive margins for peripheral vascular disease
Predicted mean number of complications
Age group
pres_pvd=0
pres_pvd=1
Predictive margins for peripheral vascular disease
Predicted mean number of complications
Sex
pres_pvd=0
pres_pvd=1
Predictive margins for psychoses
Predicted mean number of complications
Age group
pres_psych=0
pres_psych=1
Predictive margins for psychoses
Predicted mean number of complications
Sex
pres_psych=0
pres_psych=1









STROBE Statement—Checklist of items that should be included in reports of ***cohort studies***

	Item No	Recommendation
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract – **Title page**
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found – **Methods and results**
Introduction		
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported – **Background – Sec 1 (first three paragraphs) & rationale – Sec 1 (last paragraph)**
Objectives	3	State specific objectives, including any prespecified hypotheses – **Sec 1.1, no hypothesis tests were conducted**
Methods		
Study design	4	Present key elements of study design early in the paper – **Sec 2.1**
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection – **Sections 2.1 to 2.3**
Participants	6	(*a*) Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up – **Eligibility and selection (Sec 2.3), sources (Sec 2.1) & follow up methods (Sec 2.2)**
		(*b*) For matched studies, give matching criteria and number of exposed and unexposed – **Not relevant**
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable – **outcomes (Sec 2.3.1.1), predictors (sections 2.3.1.2 & 2.3.1.3). Confounders and effect modifiers were not dealt with as the objective of the study was to derive comorbidity indices, and therefore factors on the causal pathway were not a priority.**
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group – **All variables were sourced from a single source for each state (Sec 2.1) while the socio-economic decile mapping is explained in section 2.3.1.2.**
Bias	9	Describe any efforts to address potential sources of bias – **Registry data were used; inherent biases could not be addressed. Data limitations have been discussed in detail in section 4.2.2 & 4.2.3.**
Study size	10	Explain how the study size was arrived at – **Population study, no sampling was required**
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why – **Most groupings were chosen based on standard publications. Details were not included in order to contain the word count. Details can be found in our previous paper (Fernando et al. 2019, [ref 9]).**
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding – **Sec 2.4**
		(*b*) Describe any methods used to examine subgroups and interactions – **interactions in section 3.2 and subgroups in section 3.4**
		(*c*) Explain how missing data were addressed **– Data sources were standard administrative data, therefore all variables used for analysis were well populated.**
		(*d*) If applicable, explain how loss to follow-up was addressed – **The only loss to follow-up will incur due to data-linkage. Data collection or linkage was not**

		conducted by the research team, however, false negative rates are discussed under data linkage (section 2.2).
		(*e*) Describe any sensitivity analyses **– Sensitivity analysis was not required**
Results		
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed - **Provided in the column headings or table notes for each table. Exposure and non-exposure (i.e., presence of comorbidity vs no comorbidity) provided in table 1 and table 2.**
		(b) Give reasons for non-participation at each stage- **Not applicable in these administrative databases**
		(c) Consider use of a flow diagram – **Not deemed necessary**
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders – **Provided in section 3.1. Exposure and non-exposure (i.e., presence of comorbidity vs no comorbidity) provided in table 1 and table A5.**
		(b) Indicate number of participants with missing data for each variable of interest – **Not found in these administrative data sets**
		(c) Summarise follow-up time (eg, average and total amount) – **Provided in section 2.3.1.1. ICU and MV hours were for the index admission (i.e. the index record and all subsequent records for that incident), maximum follow-up time being two years. For hospital-acquired complications, it was the index admission and all related readmissions followed up for six months for every patient in the database.**
Outcome data	15*	Report numbers of outcome events or summary measures over time – **Provided in section 3.1. Exposure and non-exposure (i.e., presence of comorbidity vs no comorbidity) provided in table 1.**
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included – **Due to the magnitude of results required to explain the findings (therefore extending the size of the manuscript), unadjusted estimates are not provided. They are available in a former publication by the same authors (Fernando et al. 2019, [ref 9]). Adjusted estimates are provided in the relevant tables (tables 4,5, A1, A2, A4 & A7).**
		(*b*) Report category boundaries when continuous variables were categorized – **Standard boundaries were applied. E.g., age groups (other published literature), injury severity (ICISS- Sec 2.3.1.2).**
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period – **Not provided**
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses – **Internal (Sec 3.4) and external (Sec 3.5) validations and interactions (Sec 3.2) provided. Interaction plots provide in Appendix A2.**
Discussion		
Key results	18	Summarise key results with reference to study objectives – **Provided in section 4 paragraph 1.**
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias – **Provided in section 4.2.**
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations,

		multiplicity of analyses, results from similar studies, and other relevant evidence- **Provided in section 5.**
Generalisability	21	Discuss the generalisability (external validity) of the study results- **Discussed in detail under section 3.5 of the results section, therefore not elaborated further in the discussion.**
Other information		
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based- **Provided under "Funding".**

*Give information separately for exposed and unexposed groups.

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

7 The overall performance of the Australian Injury Comorbidity Indices

The aim of this chapter is to compare the comorbidity indices derived in the last three chapters for mortality, burden and in-hospital complications with each other, as well as compare with the Charlson comorbidity index (CCI) and Elixhauser comorbidity measure (ECM). The comparisons are made with regard to the parsimony, comorbidities included and the gain in predictive ability over a baseline model.

The research question that will be answered in this chapter is:

Can the effect of comorbidity be generalised across a range of outcomes?

Chapter 3 showed that an increase in the *number* of comorbidities increased the likelihood of adverse outcomes, but the relationship between specific comorbidities and the outcome varied with the outcome, answering the above question in terms of the count of comorbidities. Chapters 4, 5 and 6 showed that each outcome was associated with a selection of comorbidities, and only in some instances was it possible to derive parsimonious indices that work across a group of outcomes. This chapter compares the *type* of comorbidities associated with outcomes which further demonstrates that the associations cannot be generalised across a range of outcomes.

7.1 Parsimony and comorbidities included in the new and existing indices

Table 7-1 shows that the number of comorbidities associated with each outcome varies from 2 to 28 within the 31 conditions considered in this study. In comparison, the CCI consistently uses 19 conditions (becomes 17 when lymphoma

and leukemia is bundled with ‘any malignancy’) and the ECM applies 31. As an example, HIV/AIDS has no bearing for any of the outcomes according to the Australian injury comorbidity indices (AICIs), but both the CCI and ECM include it, with the CCI allocating one of its highest weights (weight not shown in the table). This is also true for rheumatic disease (though the weight allocated for this in the CCI was one of the lowest).

For in-hospital and 30-day mortality, CCI and ECM would appear to be unnecessarily resource-intensive compared to the AICIs, in terms of the number of comorbidities needed to calculate the indices. For 1-year mortality, the CCI seemed closer to the AICI, while the ECM was still relatively resource intensive. The CCI was derived for 1-year mortality, which could explain its relevance to the setting. Alternatively, the ECM was derived for in-hospital death and therefore a closer alignment with the AICI-hd (AICI for in-hospital death) can be expected. But, the fact that the ECM was also derived for LOS and costs, could be the reason that the ECM captures more conditions than the AICIs. Conditions such as malignancies, metastasised tumors, and renal disease are shown to be associated with all mortality outcomes in *all* new and existing indices. However, disease groups likely to be associated with the outcomes *also* include heart conditions, dementia and liver disease according to the *new* indices.

Burden outcomes were associated with far more comorbidities than those associated with mortality outcomes. Combining conditions from both the ECM and CCI, has resulted in more conditions in the AICIs which are relevant to burden outcomes; the CCI alone does not contain some of the conditions relevant to burden outcomes. This could be a reason why some studies in the past found the CCI to perform poorly for resource utilisation [33]. In contrast, the ECM was derived with the

aim of predicting resource utilisation outcomes as one of its objectives. For burden outcomes, the groups of diseases likely to be associated with the outcomes were substance dependence, malignancies, heart diseases, blood conditions, diabetes, liver disease, mental illnesses, renal and rheumatic conditions. Previous studies have shown that conditions such as psychoses, drug and alcohol dependence and hypertension were not related to mortality [55] but were associated with LOS and costs [57], similar to the findings of this study (Table 7-1).

Readmissions outcomes, similar to mortality outcomes, showed associations with fewer comorbidities than burden outcomes, with the CCI and ECM including an unnecessarily long array of comorbidities for these outcomes. Readmissions were associated with alcohol dependence, diabetes, liver disease, psychoses and renal disease.

The use of the ICU and the mechanical ventilator (MV) and their association with comorbidities cannot be as clearly explained, except for chronic pulmonary disease and coagulopathy, which are conditions related to breathing and blood-clotting. Fourteen of the 15 comorbidities associated with the CHADx (classification of hospital-acquired diagnoses) complications were also seen in the ECM, while only 7 conditions from the CCI aligned with the AICI. Conditions associated with CHADx complications were heart disease, alcohol dependence, blood conditions, breathing problems, mental illness, liver disease, obesity and renal disease. However, it must be noted that the association is with the *number of* complications. The type of CHADx complication makes a difference as to what conditions are associated with it, as some of the sub-analysis in Chapter 6 has shown.

Overall, for mortality outcomes, the AICIs are more parsimonious than the CCI and ECM, while being sufficient in terms of relevant conditions included. The ECM is

relatively resource-intensive for predicting mortality given it has 30 conditions to adjust for, while mortality is mainly driven by age and injury severity. For burden, the AICIs and ECM are close in parsimony (the AICIs are inherently missing three comorbidities from the ECM) and relevance, while the CCI lags behind with some relevant comorbidities omitted. For readmissions, the AICIs and ECM are more suitable than the CCI as some of the conditions found to be associated (psychoses, alcohol dependence) are those from the ECM, therefore the CCI will fail to capture the effects of relevant conditions on the outcomes. The ECM and AICI perform better than the CCI for complications when considering possible associations, as discussed previously, while the complication-specific AICIs derived in this study could be the most suitable of all.

It is clear that one cannot derive an index that works across all outcomes, as there was only one condition (coagulopathy) that was common to all outcomes (Table 7-1).

7.2 Gain in predictive power

Overall, the small gain in predictive power that can be attained by adding an index such as the CCI to baseline models seen in this study are similar to those seen in the past (explained below). Given this is a small increment, it demonstrates that other variables are more dominant in driving these outcomes.

Table 7-2Table 7-2 shows the gain in predictive power achieved by adding each comorbidity index to the baseline model. Some gains were based on the AUCs and some on R^2, but all were less than or equal to 5%. As discussed in the previous chapters, the demographic and injury characteristics (baseline variables) accounted for most of the variation explained by the models. On average they accounted for 85%

or more of the total variation that could be explained by any of the full models, including comorbidity. The highest gain by adding a comorbidity index was seen for predicting hospital costs, followed by in-hospital death, ICU stay and MV use.

The CCI seemed to do well for 1-year mortality, which is expected as it was derived for that purpose, and as confirmed in other studies [25, 33, 58, 59]. Table 7-2 also shows that the CCI was weakest for predicting complications and burden.

From Table 1 in the publication attached to Chapter 1 [1] (the literature review), it was seen that in certain studies [60, 61], adding the CCI to the baseline model for predicting in-hospital death for injury patients produced a predictive gain of about 3% or less, which is similar to what was observed in the current study (Table 7-2). In the same table (Table 1 in the paper attached to Chapter 1) the gain for hip-fracture patients [33] was 7-11%, which is similar to that seen from the subgroup analysis in chapter 4 (Table A4 in paper attached to chapter 4).

For readmissions within 30 days, Table 1 in the literature review (paper attached to chapter 1) shows that among hip-fracture patients [33] the predictive power of the baseline model was around 55%, and the gain in power by adding the CCI was only about 1%. The current study also shows similarly that the baseline predicts about 58% and the CCI adds around 2% (Table A4 in paper attached to chapter 5).

Overall, these results indicate that the predictive abilities found in the different indices in this study align well with past research when comparisons could be made reliably, and that the gains in adding these indices are small compared to what the non-comorbidity variables contribute to outcome prediction.

7.3 Conclusion

In conclusion, although certain outcome-group specific comorbidity indices (such as the AICI-m (mortality), AICI-b (burden) or AICI-r (readmission)) can be derived, a more general comorbidity index that can be used reliably across all injury outcomes is not feasible

Table 7-1: The suite of Australian Injury Comorbidity Indices, the CCI and ECM

Comorbidity	Mortality (AICIs)				Burden (AICIs)				Readmissions (AICIs)			Complications (AICIs)			1-year mortality (CCI)	In-hospital death /LOS/cost (ECM)
	In-hospital	30-day	1-year	**All mortality**	Overnight stay	LOS	Cost	**All burden**	All-cause	Non-planned	**All readmissions**	ICU hours	MV hours	Complications		
Total number of conditions	**11**	**13**	**19**	**10**	**24**	**27**	**28**	**23**	**10**	**11**	**8**	**5**	**2**	**15**	17	30
HIV/AIDS															✓	✓
Alcohol dependence					✓	✓	✓	✓	✓	✓	✓		✓	✓		✓
Drug dependence			✓		✓	✓	✓	✓		✓						✓
Any malignancy	✓	✓	✓	✓	✓	✓	✓	✓	✓						✓	✓
Blood loss anaemia					✓	✓	✓	✓								✓
Cardiac arrhythmias	✓	✓	✓	✓	✓	✓	✓	✓						✓		✓
Cerebrovascular disease		✓				✓									✓	
Chronic pulmonary disease	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
Coagulopathy	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
Congestive heart failure	✓	✓	✓	✓	✓	✓	✓	✓		✓				✓	✓	✓
Deficiency anaemias			✓		✓	✓	✓	✓								✓
Dementia	✓	✓	✓	✓	✓		✓							✓	✓	
Depression					✓	✓	✓	✓	✓			✓		✓		✓
Diabetes with chronic complications			✓		✓	✓	✓	✓	✓	✓	✓			✓	✓	✓
Diabetes without complications			✓		✓	✓	✓	✓	✓	✓	✓				✓	✓
Fluid and electrolyte disorders	-	-	-	-	-	-	-	-	-	-	-	-	-	-		✓
Hemiplegia/paraplegia			✓		✓	✓	✓	✓							✓	✓
Hypertension complicated							✓									✓
Hypertension uncomplicated					✓	✓	✓	✓				✓		✓		✓
Hypothyroidism					✓	✓	✓	✓								✓
Metastatic solid tumor	✓	✓	✓	✓		✓				✓					✓	✓
Mild liver disease	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓	
Moderate or severe liver disease		✓	✓		✓	✓	✓	✓						✓	✓	✓
Myocardial infarction	✓	✓	✓	✓			✓								✓	
Obesity					✓	✓	✓	✓				✓		✓		✓
Other neurological disorders	-	-	-	-	-	-	-	-	-	-	-	-	-	-		✓
Peptic ulcer disease	✓					✓	✓								✓	✓
Peripheral vascular disease		✓	✓		✓	✓	✓	✓						✓	✓	✓
Psychoses			✓		✓	✓	✓	✓	✓	✓	✓			✓		✓
Pulmonary circulation disorders			✓			✓	✓									✓
Renal disease including renal failure	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓	✓
Rheumatic disease including some other conn					✓	✓	✓	✓							✓	✓
Valvular disease					✓	✓	✓	✓						✓		✓
Weight loss	-	-	-	-	-	-	-	-	-	-	-	-	-	-		✓

Table 7-2: Gain in predictive powers for the new AICIs, CCI and ECM by outcome

Index	Mortality			Burden			30-day		Complications		
	In-hospital (AUC)	30-day (AUC)	1-year (AUC)	Overnight stay (AUC)	LOS (R2)	Cost (R2)	All-cause (AUC)	Non-planned (AUC)	ICU hours (R2)	MV hours (R2)	CHADx Complications (R2)
Baseline	89%	91%	90%	75%	8%	31%	61%	62%	10%	14%	3%
AICI adds	3%	2%	1%	1%	1%	5%	1%	1%	2%	2%	1%
CCI adds	2%	1%	1%	0%	0%	2%	1%	1%	0%	0%	0%
ECM adds	3%	2%	1%	1%	1%	5%	2%	2%	3%	3%	1%
Average proportion of variation explained by baseline when any index is added	97%	99%	99%	99%	92%	89%	98%	98%	88%	89%	85%

8 Discussion

The main aim of this chapter is to provide an in-depth discussion on what this thesis was able to achieve, along with its strengths, limitations, and some provisional thoughts for future work in the topic area. It will begin with a recap of the rationale for the study followed by a summary of findings in terms of the main research question. The rest will be discussed in themes that are of particular importance to the thesis.

8.1 Rationale and aim

Existing comorbidity indices which were derived using general medical patient data, mainly for predicting mortality outcomes, are widely used in injury epidemiology without much consideration of their relevance to injury populations, to the outcomes being assessed, nor considering recent advances in medical science. Past evidence indicates that general injury- and outcome-specific comorbidity indices had not been derived for hospital-admitted injury patients. Hence, it was uncertain, should such specific indices exist, whether they would be better predictors of outcomes compared to the existing measures. Therefore, better prediction of outcomes by indices specifically derived for injury populations motivated the current project. The main question[5] this thesis set out to answer was:

How does comorbidity affect outcomes of hospitalised injury patients in Victoria and can the impact of comorbidities effectively be captured in a summary index?

[5] The subsidiary questions have all been addressed in the previous chapters and are not stated here to avoid repetition

8.2 Summary of findings

The thesis consisted of two components, a literature review and subsequent data analysis, both informing the main research question. The literature review was conducted to identify outcomes that can be readily measured and coded using hospital administrative datasets, limited to those that reasonably reflect the effects of comorbidities. The review also identified other factors (socio-demographic and injury) that were likely to affect these outcomes, as well as appropriate methods for identifying and coding comorbidities. A study of the evolution of comorbidity measures since the 1950s to date, and an evaluation of the most widely used comorbidity indices' performances in terms of their ability to predict outcomes were included in the review. For the purposes of this research, cited studies were most relevant since the need was to identify comorbidity indices and how they have been applied. Using the search methods outlined in chapter 1, it is unlikely that any well-cited studies on comorbidity and injury were missed.

The second component was a data linkage study of hospital admitted injury patients. Based on the learnings from the review, and using linked data, an initial descriptive analysis was carried out to describe the outcomes in a Victorian hospital-admitted injury patient cohort. This was followed by a univariate analysis to establish associations between outcomes, and socio-demographic factors, injury characteristics and comorbidity. At this point it was established that **an increase in number of comorbidities was associated with adverse outcomes.**

Following this, multivariable regression analysis was conducted, focussing on three specific groups of outcomes, namely mortality, burden and complications. Various forms of comorbidity quantifications were modelled and their accuracy in

outcome prediction assessed. They were: the presence of at least one comorbidity, count of comorbidities, presence of each comorbidity, and existing comorbidity indices such as the weighted CCI and the binary ECM. **At this point, a suite of new outcome- and injury-specific comorbidity indices, called the Australian injury comorbidity indices (AICIs) were derived, being a key outcome from the thesis. The novelty of the AICIs is that they include only the comorbidities found to have a statistically significant association with the outcome of interest, derived using population level data specific to hospital-admitted injury.** Based on the analysis carried out to derive the new indices, it was also concluded that the binary form of comorbidity representation was as good (or even better in some instances) as a weighted index in terms of predicting outcomes.

A single summary measure suitable for all outcomes (i.e., mortality, burden and complications) could not be derived given the wide variation in comorbidities associated with each of them. Summary measures specific to particular outcomes, however, such as for mortality, LOS and cost, and readmissions, were derived without much loss in predictive power compared to the individual indices. For example, the individual index for all cause 30-day readmission had slightly (but not significantly) better predictive power over the summary index for all readmissions. However, the two summary measures for mortality and readmission resulted in a higher number (though not statistically significant) of erroneously predicted outcomes (i.e., false negatives) compared to the individual indices.

Age and injury characteristics were found to be the dominant predictors of most outcomes among hospital-admitted injury patients. On average they accounted for 85% or more of the total variation that could be explained, even post-addition of

comorbidity in regression models. Yet, adjusting for comorbidities which are either covariates or confounders is crucial in clinical processes and injury research. Although not the primary predictor, the indices still have predictive power and can potentially change how treatment is administered or adjustments for comorbidity are made in research.

The comorbidity indices derived in this thesis for specific outcomes were equal to or in certain instances outperformed the existing indices in terms of predictive ability. In addition, they also outperformed existing indices in terms of relevance and parsimony. Another key finding of this thesis was that the magnitude of the effect of these conditions on the outcomes (as assessed in the AICIs) were different to what the CCI attributes, i.e., the comorbidity weights were different. The binary AICIs with a shorter list of conditions are easier to use over a weighted index such as the widely used CCI, and more parsimonious than the other widely used binary index, the ECM, which has a list of 30 conditions. Apart from this, a major contribution of this thesis to the knowledge base surrounding comorbidity indices was that it was able to validate the widely used CCI and ECM in large population cohorts and various subgroups of injury populations, for a range of outcomes.

Various recommendations have been made in the past to derive outcome- and population-specific indices [26-32]. Moor et al. (2008) [35] specifically mentioned that when deriving comorbidity scores using empirical data, it would be important to use large, representative datasets with ‘good quality’ data, making certain that they were robust when baseline characteristics change or when the trauma group differs (subgroups). This thesis addressed all these recommendations in that it: (1) provided specific indices, (2) used population level, consistently coded data, (3) validated to a

certain extent on external datasets from two other Australian states and (4) validated within subgroups.

Overall, the aim of the project was to derive indices that captured the effect of comorbidities on mortality, burden and complications related injury outcomes. Ten specific indices were derived, and each index was found to be clearly different to the others, supporting the initial postulation of this study: the effect of comorbidities vary with the outcome of interest. This finding is not particular to this study as Elixhauser et al. (1998) [22], Thompson et al. (2010) [31] and Toson et al. (2015) [33] have also shown the same. In summary, one index does not fit all outcomes, and that is the main reason this study derived outcome-specific indices. The implications are that whichever index the user chooses, they must be aware of the predictive powers (or the capability of the index to adjust for comorbidity), index validation and limitations.

The following sections discuss certain themes that emerged from this thesis, significant study limitations that were not discussed in the preceding chapters and future directions.

8.3 Comorbidity

This section discusses how the capture, prevalence and relationships between comorbidities are likely to affect the study results. It also includes a brief discussion on new comorbidities that can arise as a result of adverse injury outcomes.

8.3.1 Capture of comorbidities

8.3.1.1 The use of administrative data vs medical chart review

The method used for capturing comorbidity affects the estimated prevalence and consequently the index derivation, and outcome prediction. Conclusions drawn

from this study are discussed in the following section, in the context of justification of the methods used for capturing comorbidity and their limitations.

There has been debate about how well comorbidities are captured in administrative databases as opposed to medical chart review. Lee, Donovan and Austin (2005) [62] and Stavem, Hoel, Skjaker and Haagensen (2017) [63] stated that comorbidities had a lower prevalence when captured using administrative data vs medical chart review, while Nguyen et al. (2018) [64] and Price, Estrada and Thompson (2003) [65] concluded no notable differences. Nguyen et al.'s work [64], specific to Victoria, found that mental health, drug- and alcohol-related comorbidities captured using medical chart review were *not clearly better* in predicting outcomes compared to using ICD-10-AM coded data from a specific administrative (registry) database. Meanwhile, some of the same authors from Nguyen et al.'s group, Daly et al. (2019) [66] carried out a study to compare medical chart review with the Victorian orthopaedic trauma outcomes registry (again ICD-10-AM coded administrative data), for obesity, heart disease, arthritis, hypertension, diabetes and other diseases. They concluded that there was a *significantly higher* prevalence of obesity, osteoarthritis, ischemic heart disease and hypertension with chart review identified compared to administrative data. They also found an equal prevalence of diabetes type 2 and found that recording of coronary artery disease was absent from medical chart data.

Given the varying findings above, it is still unclear if comorbidity capture in administrative data would be clearly poorer compared to chart review for predicting outcomes in a *large general injury* cohort. In the main hospital administrative databases in Australia such as the VAED, the APDC or the HMDC (all datasets used in this study), capturing comorbidity using the combination of the condition onset flags and ICD-10 diagnosis codes is possibly one of the only justifiable means of capturing

comorbidity prevalence. However, there may be under-reporting of the actual prevalence, which remains a study limitation. Addressing this issue (i.e. improving capture of comorbidity) may affect the derivation and performance of the comorbidity indices. Conducting a comparative study of comorbidity capture among general injury patients using administrative data and medical chart review, using conditions included in the comorbidity indices, would be useful. Should they be significantly different, then a change in the composition of the AICIs could result, as well as validations of the CCI and ECM.

8.3.1.2 Introduction of the supplementary disease codes in the Australian hospital admissions data

The newly introduced mandatory collection of supplementary codes for chronic diseases for Australian hospitals may affect comorbidity capture. Starting in the financial year 2015/16, Australian hospital administrative databases and medical charts are required to record a set of supplementary codes (using ICD-10-AM) for chronic diseases. These codes are now collected in addition to the disease codes already included. A code range of U78-U88 are allocated to these conditions and in the administrative datasets they are marked as part of the 40+ diagnosis codes. However, the index episodes used in the current study (date range 2006/07 to 2013/14) excludes this time period (comorbidity capture limited to conditions present at point of hospital admission), therefore these new U-codes have not been utilised.

Nonetheless, it should be acknowledged that these supplementary codes may add value to this type of work. Daly et al. (2019) [66] conducted a review of comorbidity capture pre- and post-change and concluded that obesity, osteoarthritis and all cardiac conditions were better recorded in medical chart review than in administrative data,

after the introduction of these mandatory supplementary codes. Type 1 diabetes capture increased in both data sources post-change, but the prevalence became equal in the two data sources after the change. This implies that the introduction of the new codes is able to provide a more accurate capture of the condition. Capture of type 2 diabetes on the contrary decreased after the coding change, but the prevalence of recorded diagnoses was equal in both data sources. This could imply that the condition was over-reported previously. They also noted a substantial increase in osteoarthritis, type I diabetes, ischaemic heart disease and hypertension in administrative data post-coding changes. These findings indicate that the capture of comorbidities would benefit from the inclusion of the new supplementary U-codes.

Apart from these, there were other drawbacks of comorbidity capture, which were discussed as limitations in the paper attached to Chapter 3. Further, the drawback of not including *lookback periods* was discussed in the paper attached to Chapter 4. Lookback periods are a time span preceding the current episode, in which records from other hospital admissions for the same patient are retrospectively assessed to identify comorbidities not mentioned in the current record. Below are some reasons why lookback periods were not found to be significant for this study.

1. The main intention for the use of these indices was to use them at the point of hospital admission to help risk-stratify patients. Live data linkage nor retrospective data linkage is available in most clinical settings. Even in epidemiological research, the usage of retrospectively linked data is still limited. The intention with this study was to provide an index that is suitable for most settings and therefore should have a wide applicability.

2. Two Australian studies have shown that the inclusion of lookback periods did not increase comorbidity capture by and large, nor did they have a significant

impact on most outcomes. Toson et al. (2015) [33] showed that by including a 1-year lookback, the overall capture of comorbidities increased by 10% in their study of hip-fracture patients over the age of 65 years in the state of New South Wales, which is quite a similar population in size and structure to Victoria. They also found that the lookback-period inclusion only impacted the predictive power of the Charlson indices for the outcome of 1-year mortality, and not for readmissions. Preen et al. (2006) [59] suggested that a 5-year lookback period would likely pick up more comorbidities among general medical patients for readmission outcomes.

3. It is likely that all pertinent comorbidities will be recorded in the index admission. The administrative data used were known to contain all comorbidities that are actively monitored or treated during the hospital admission. A lookback will bring in comorbidities that were relevant (actively monitored) at the previous admission, which may be resolved or not pertinent to the present admission.

4. In addition, when using lookback periods, care should be taken to be mindful of comorbidities that might be transient (such as obesity and alcohol dependence) so care would need to be taken to identify such comorbidities and identify the timeframe over which they might be transient.

5. This study was conducted using a ‘follow-up’ and not a ‘look-back’ dataset, therefore is not best placed to do a lookback analysis. However, a lookback analysis was undertaken with a subset of the data (from the follow-up data) and re-running the modelling. This lookback analysis of a smaller sample using the follow-up admissions revealed that the capture of comorbidity increased by about 28%, and the number of patients with comorbidities increased only from

19% to 21%. The increase came from mostly the same patients but only increased the number of comorbidities in these patients. Presented below are the results of this analysis where the outcome of in-hospital death was modelled using the same baseline variables (derivation model) as in chapter 4 (age, gender, injury type and injury severity). Table 8-1 shows that there is little difference in the predictive powers or the kind of comorbidities that are associated with the outcome between the 'non-lookback' and 'lookback' analysis. It must be noted that this is based on a follow-up data extraction (not a lookback), and therefore only 55,000/161,334 persons could be included.

Table 8-1: Lookback analysis for in-hospital death (number of comorbidities and predictive power)

Comorbidity capture	Number of comorbidities in binary model	AUC statistic	Comment
Last admission only	10	94.36	
Last admission + previous admissions in the preceding 12 months (1-year lookback)	8	94.11	Cardiac arrythmia and myocardial infarction eliminated during the backward-elimination process here. However, the process is based on an AIC statistic difference of 10 or more between the larger and smaller models. These two conditions came at a difference of 9 and 8 from the parent model, which are close to the cut-off of 10; therefore, one could even argue retaining them.

It could also be seen (

Table 8-2) that this additional inclusion of comorbidities doesn't result in a higher proportion of patients with the comorbidity who then have an adverse outcome. Possibly, the look-back period is more sensitive in identifying less-severe (or resolved) conditions. Therefore, causes in-significant differences to the results.

Table 8-2: Proportions of patients with the comorbidity and the outcome for lookback vs non-lookback samples

	Proportion of in-hospital death for those with cardiac arrythmia	Proportion of in-hospital death for those with myocardial infarction
Last admission only	18%	38%
Last admission + previous admissions in the preceding 12 months (1-year lookback)	16%	27%

Based on what is presented above, it is unlikely that using a lookback period to identify comorbidities would result in a more effective and relevant index.

Overall, the limitations with comorbidity capture can be addressed by using: (1) medical chart review (although this is relatively costly and time-consuming) or self-reports (not discussed in detail in this thesis, but care should be taken to minimise biases in self reports), (2) data post-2015/16 with the supplementary U-codes and (3) lookback periods (to a much lesser extent as most likely they are useful in the context of index diseases rather than injury, where diseases are more likely to be associated with long-term comorbidity).

8.3.2 Prevalence of comorbidities

The prevalence of comorbidities in the study cohort determines which conditions are included in the indices, which in turn affects outcome prediction. Understanding how prevalence affects outcome prediction is important. There are two concerns to be addressed with regard to prevalence: (1) the proximity of the prevalence of comorbidities captured in this study to the actual comorbidities present in the population and (2) the impact of the comorbidity-prevalence on the statistical power of detecting associations with the outcomes.

8.3.2.1 Prevalence of comorbidities captured in the study

The overall prevalence of comorbidity captured in the current study aligned well with published Australian figures (paper attached to chapter 3) and Canadian figures [35], with the proportion of adults with at least one comorbidity in this study of 22.6% being close to the 25.5% observed in Canada.

Thirty-one comorbid conditions were discussed in chapters 4, 5 and 6. Of these, the top-nine most prevalent conditions for all three states of Victoria, NSW and WA were the same, i.e., alcohol dependence, diabetes with and without complications, uncomplicated hypertension, cardiac arrythmias, renal diseases, dementia, depression and drug dependence, all with a prevalence of more than 1% (proportions can be found in tables 2 and A5 in the paper attached to chapter 5). Hospital admissions data for WA had a higher rate of recorded alcohol and drug dependence, but lower rates of uncomplicated hypertension, cardiac arrythmias and depression compared to the other two states. Both these points imply that similarities and dissimilarities exist across states with regards to recorded comorbidity prevalence. This could be due to an actual difference in the prevalence of some conditions in different areas or be related to variations in comorbidity capture.

A reliable comparison of prevalence by type of comorbidity in the study cohort with other similar national statistics could not be carried out. Hospital-recorded comorbidity rates by age and sex were quite different to prevalence of chronic diseases in the population. The latter can be found, but was not a reasonable comparison as some of the national-level statistics currently published for a few comorbidities were based on self-reports and collected for different purposes than hospital-administrative use, and they did not directly align with the types of comorbidities used in this study.

Comparing comorbidity prevalence among injury populations from studies in Canada [35] and the USA [31] (both of which were around a decade old), the prevalence captured in this study was far lower for all but three of the 31 conditions studied. Diabetes without complications, mild liver disease and metastasised solid tumors showed very similar prevalence with the said two studies. The data for the former two studies were sourced from trauma registries (possibly more severe cases and the data assembled more rigorously) while data for the current study were from administrative databases that cover trauma and non-trauma patients. Therefore, the level and accuracy of comorbidity captured in the data from the current study maybe different due to the effect of the type of data collection. Further, the comorbidity prevalence in the current study was quite low compared to a more recent study from the USA (Calvo et al., 2016) [67]. However, the US study was based on patients from a level 1 trauma centre who were 55 years and older, which could possibly mean a higher proportion of severe trauma patients and likely to have higher comorbidity prevalence due to age.

Therefore, at this stage, it is not possible to conclude that the prevalence of each comorbid condition estimated in this study was close to the prevalence in the population at large or even in the injury population. However, the prevalence of the top nine comorbidities across three states in Australia was captured to an extent that was sufficient for the purpose of this research, i.e. for studying the impact on injury outcomes. It should also be noted that the local prevalence of the comorbidity is not necessarily relevant for constructing the index, except when the overall impact of a comorbidity differs substantially between various populations, for example the impact of sickle cell disease in Nigeria vs. Australia. Comorbidities that have a profound impact on injury outcomes may not be incorporated in the comorbidity index if the

prevalence in the population at hand is very low, due to insufficient statistical power. This is discussed in more detail in the next section.

8.3.2.2 Comorbidity prevalence and its effect on comorbidity indices

The new and existing comorbidity indices were derived based on specific study populations. That is, the new indices were derived using injury populations, while the CCI and ECM were derived using general medical patients, which include injury and non-injury patients. The prevalence of comorbidities in the two groups (injury only vs general patients including injury cases) could be very different. For example, Cameron et al. (2005) [13] and Mitchel, Cameron & McClure (2017) [12] found that comorbidity prevalence was higher among injury patients than non-injury patients. The prevalence of comorbidities in a specific patient population would impact on which conditions are included in the indices. When these indices are applied to populations with different chronic disease profiles, they may be inadequate at providing the best comorbidity adjustment for that population.

For example, in the current study population of general injury patients in Australia, conditions such as HIV/AIDS had very low prevalence. Hence, for the new index derivation, this condition did not rank highly based on the inclusion criteria compared to some of the other more prevalent conditions such as coagulopathy, liver and renal diseases. In deriving the new indices, conditions were included in an index based on two factors: its prevalence in the data/population, and its impact on outcomes. Therefore, some conditions may have had great impact but were insufficiently represented to merit inclusion in the index.

Another example is obesity, which was not recorded well in Australia. If one were to use the CCI or the AICI in the USA for instance, where obesity prevalence and

recording could be higher than in Australia, the results would not be adjusted for this important comorbidity, as these two indices do not include obesity. Obesity has been found to be an independent risk factor for mortality after trauma as suggested in past studies [68, 69], but, Moor et al. (2008) [35] (a Canadian study) and the current study found to the contrary, that obesity had no impact, which both studies acknowledge could be due to low prevalence or underreporting. Similarly, if one were to use the AICIs in Africa for instance, the impact of HIV/AIDS would not be captured, though it could be cause for significant burden or mortality in that region. Further, none of these indices (AICIs, CCI or ECM) would work well in regions with high prevalence of malaria or sickle cell disease, for example. Potentially these conditions could have huge impacts on outcomes but were not picked up in data from Australia and North America (where the indices were derived), because of local low prevalence. This suggests a need to adapt the indices to the local context based on local data. In such instances, making a judgement call at the time of application and including them may be beneficial in a population where the condition is likely to be more prevalent and the condition likely to be more relevant to the outcome. If this cannot be done, the existing or new indices could be the next best options provided they are used with caution. Clinical/logical input may be required to make reasonable judgement on whether certain conditions should be included/excluded when using a particular index based on relevance to the particular population.

In populations with a high prevalence of certain diseases that are not directly relevant to the outcome, the conditions could still have an impact on the overall burden related to the outcome due to their high prevalence. In such instances, the inclusion/exclusion of these conditions depend on the outcome of interest. For example, in a study like the current one, for burden outcomes such as costs, it is

worthwhile to include these conditions (high prevalence and not significantly associated with the outcome) in the index as they are most likely to have an impact on the cost of drugs administered. The summation of all these costs will increase the combined cost estimate. A similar argument is not relevant for an outcome such as in-hospital death.

8.3.3 Correlation between comorbidities

Correlation implies the movement of two variables, together in the same or opposing direction, and that a statistical association exists between them. However, correlation is not always causation, which implies that should a statistically significant correlation present, it would not necessarily imply that one variable causes the changes in the other. However, it might indicate that the same underlying process drives both measures.

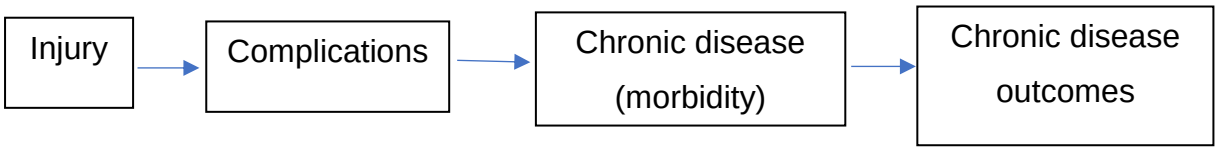
Identifying and adjusting for correlations between comorbidities is important in avoiding spurious interpretations of the relationships between comorbidities and outcomes. As mentioned in the paper attached to chapter 4, the correlations between comorbidity groups were below 0.5 for all conditions except between *cerebrovascular disease* and *hemiplegia/paraplegia* (0.5) and *metastatic solid tumor* and *any malignancy* (0.7). Even though there were correlations between these two pairs of conditions, both conditions for each pair were retained as their effects were considered independent, for the following three reasons: (1) the chosen comorbidities were from past lists (CCI and ECM) of conditions that have been used extensively and validated across many studies (which would have required them to be considered as independent of each other); (2) the use of a backward elimination process to eliminate comorbidities that no longer improved the model in this study; and (3) the mutual exclusivity of the ICD-10 codes used to identify each condition. The correlations

observed above could be considered causal; for example, metastasized solid tumors could be advanced stages of malignancy. Nonetheless, considering the three reasons presented above, it was decided to retain all these conditions in the current study when found to be significantly associated with the outcome. Furthermore, since the relationships were not being interpreted directly, and the only important criteria was the predictive power of the comorbidities in predicting outcomes, the inter-correlations did not really matter.

8.3.4 Comorbidity as outcomes of injury

Complications arising from injury could also lead to the development of chronic conditions that give rise to chronic disease outcomes or worsen injury outcomes. This aspect was not investigated in the current study. The diagram below (Figure 3) shows the sequence of such events.

Figure 3: Sequence from injury to chronic disease outcomes



An example of this is when complications arise during a hospital episode: these can lead to, for instance, mental health issues, which could impact costs, LOS and readmissions. As another example, adverse drug reactions could cause changes to blood pressure or blood glucose levels (and/or new onset diabetes type 2). These, in turn, could also impact outcomes such as costs and length of hospital stay. However, this thesis assessed the associations between *pre-existing* comorbidities and outcomes, whereas the effects of comorbid conditions that develop during hospital stay due to complications, or the subsequent development of chronic disease outcomes is an area that remains for further expansion of the work.

8.4 Outcomes

This section discusses: (1) the novelty of associations established with complications outcomes, (2) the reliability of the outcome figures derived in this study, (3) the associations between various outcomes (i.e., outcomes vs outcomes) and (4) the origin of CHADx (classification of hospital-acquired diagnoses) complications outcomes.

8.4.1 Association between comorbidity and complications among injury populations

The associations established between hospital complications and comorbidity in such detail is novel to this study. There are studies that have used comorbidity indices to predict ICU and ventilator use for all medical patients. There are no studies that have shown and quantified the association between each comorbidity and the use of these ICU services – certainly not for injury patients. Also, there are no studies that have looked at CHADx complications with comorbidity in this level of detail. For instance, the matrices in Tables 3 and A3 in the manuscript attached to chapter 6 present proportions of patients for 31 comorbidities and 17 CHADx complications, and their associations, which have not been presented before based on the literature reviewed for this study. This information is both new and useful.

8.4.2 Reliability of outcome measures

The validity of conclusions drawn from this thesis partly relies on the capture of comorbidities and their prevalence, while it also relies on the reliability of the capture of outcomes. The proportions/means/medians of outcomes estimated in this thesis should fall within published estimates of state or national-level statistics for the same outcomes. The overall proportions of most outcomes assessed in the study population

in Victoria, had a reasonably good alignment with nationally reported statistics (Chapter 3). When they differed, it was possible to attribute the differences to improved capture achieved by using data linkage in the current study, or to differences in patient cohorts. Given that the overall outcomes were comparable with previously published statistics, it is expected that the conclusions drawn, and indices derived and validated are based on reliable and representative measures of the outcomes.

8.4.3 Outcomes as predictors of other outcomes

Past studies have shown that certain outcomes during hospital stay are predictors of other outcomes [70-72]. Some examples are the associations of LOS with costs, MV use with mortality, and MV use with complications. These associations between predictor outcomes and response outcomes were assessed in the univariate analysis component of this thesis and presented in chapter 3.

Complications for instance increased the likelihood of in-hospital death, costs, LOS and the use of critical care services (e.g., ICU, MV and cardiac care unit (CCU)), therefore could be a useful predictor variable in predicting the latter outcomes. Such information could be used to prevent the secondary outcome by putting measures in place to reduce the impact caused by the primary outcome.

It was also seen that an in-hospital complication (e.g., CHADx, ICU, MV or CCU use) could influence another in-hospital complication, but not vice versa. For example, it was seen that CHADx complications (hospital-acquired complications) were associated with stays in the ICU, MV or CCU, whereas only the use of the MV was associated with CHADx complications. This implies that adjustments for irrelevant predictor variables could be avoided with the availability of this kind of information. Overall, an important contribution from this thesis to the existing knowledge base was

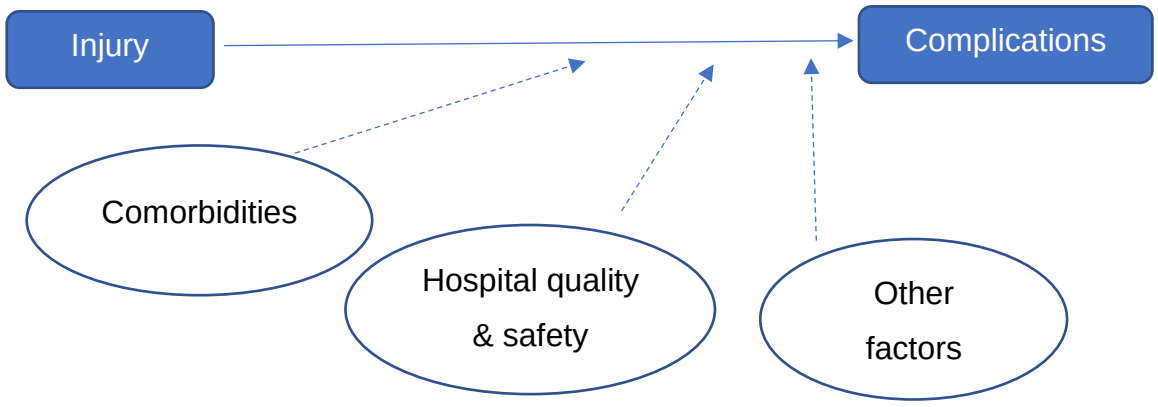
this *matrix* of associations between outcomes for hospital-admitted injury patients. This type of matrix could be a valuable source of information for secondary prevention of outcomes as explained above.

8.4.4 Origins of CHADx complications

The analysis of associations between comorbidities and hospital-acquired complications was one of the more novel components of this thesis. This sort of analysis on injury or non-injury patients has rarely been documented, except for a few noted studies [16, 73-75].

The classification of hospital-acquired diagnoses (CHADx) was used to identify complications, i.e., those arising during the period of hospital care. The CHADx itself is a complex tool. Though CHADx complications are coded as occurring during the hospital stay, cause of the complications cannot always be accurately distinguished, i.e., if some of them were due to hospital care, or late manifestations of the injury or comorbidity. The diagram below (Figure 4) illustrates these possible influences. The aim of predicting complications is with the expectation that some of them could be avoided. If they are in fact late manifestations of the injury or comorbidities (rather than related to hospital-care), the potential for preventing them is low, even if they are predictable. Comorbidity indices derived for predicting hospital-acquired complications should focus on complications that are preventable. These are complication groups such as adverse drug events or those arising from medical procedures or falls in hospital. Conversely, complications such as pneumonia, the cause of which may not be easily distinguishable, would not benefit so much from a comorbidity index if prevention was the ultimate goal.

Figure 4: Origins of CHADx complications



8.5 Associations between comorbidities and outcomes

As identified in chapter 1, previous studies have recommended the derivation of outcome-specific comorbidity indices. This implies that the associations between comorbidities and outcomes vary depending on the outcome studied. This thesis clearly showed that this is the case, substantiating previous recommendations. It was evident that certain groups of comorbid conditions were associated with two or more of the outcome groups, while the rest seemed to be associated only with a specific outcome group (Chapter 7, section 7.1). For instance, heart conditions, malignancies, liver and renal diseases were common to mortality and burden outcomes, whereas substance dependence was related to burden, readmissions and complications outcomes (some of the commonality is expected given the outcomes were related to each other as noted in chapter 3). Rheumatic and valvular diseases were only associated with burden outcomes. This places emphasis on the need for outcome-specific indices. These associations established in the thesis were generally consistent with the CCI and ECM (although the weights in the weighted AICIs and CCI were different to each other), which further supports the validity of these conclusions. The matrix provided in Chapter 7 (section 7.1) can be utilised in clinical work, i.e., they

can be used to risk-stratify patients according to their comorbidities and expected outcomes.

8.6 Other comorbidity indices

A discussion on comorbidity indices is not complete unless all other major comorbidity indices (other than the ones specifically considered in this thesis) are mentioned. Apart from the AICIs, the CCI, the ECM, the Mortality Risk for Trauma (MORT) and the Multipurpose Australian Comorbidity Scoring System (MACSS) (already discussed in previous chapters), other comorbidity measures available are the Paediatric Comorbidity Model developed by Tai, Dick, To and Wright in 2006 [76], the Paediatric Comorbidity Index developed by Torres-Espíndola et al. in 2019 [77] and the Rhee Index developed by Rhee et al. in 2013 [78], all of which are for use with children. Due to the lower prevalence of comorbidities among children (though it is acknowledged that it is a growing epidemic – e.g. childhood type 2 diabetes and obesity), this thesis has not validated those indices.

The current study showed that the AICI, CCI and ECM perform similarly, based on the assessment criteria used in this study (e.g., AUCs, R^2s etc). However, the MACSS (not validated in this study) could perform even better given it has 102 conditions. However, the MACSS will be impractical to use in most settings given it has too many conditions, which could result in overfitting, and result in issues with model convergence. Finally, this thesis has not validated the MORT given that it was not a widely used index.

It is worthwhile to note that the benefits of an index are dependent on;

(1) the parsimony and practicality of the index,

(2) relevance of the index to the study population, and

(3) the impact of conditions on the outcome.

8.7 Comparison of the AICIs with trauma indices

Apart from comorbidity indices, trauma indices also provide a significant increase in predictive power in outcome prediction models. Therefore, it is important to know the expectation placed on comorbidity indices when applied to injury populations. Comorbidity indices are typically utilised as prediction tools and as adjustment tools. In settings where comorbidity plays a significant role in the outcomes, the indices are a valuable resource as a tool for predicting likely outcomes, particularly across a cohort. In instances where injury or other index conditions pre-dominantly drive the outcomes, comorbidity indices are best used to adjust for the competing risk comorbidities pose on the outcomes; which is the more common use.

Two of the more widely used trauma indices are the *Trauma* and *Injury* Severity Score (TRISS) and the International Classification of disease Injury Severity Score (ICISS). The AICIs were not compared with TRISS in this study, while the ICISS was used as a factor variable when deriving the AICIs.

TRISS scoring for injury patients is commonly used in clinical practice, but requires a particular set of data fields for computing the scores. TRISS requires abbreviated injury scale scores, systolic blood pressure, respiratory rate, coma scores etc. which are not readily available in all hospital administrative databases. Further, there are contradictory recommendations regarding the need for comorbidity adjustment with the use of TRISS [35, 60, 79]. Gabbe et al. [60] concluded that adding CCI to a model with TRISS did not improve prediction while Bergeron et al. [79] and Moor et al. [35] found that adding age and comorbidity to models with TRISS improved prediction. Therefore, comorbidity indices may still be useful in the presence of TRISS

for outcome prediction. Future extensions of the current work could include adding the AICIs to models with TRISS to test for predictive power improvement.

The ICISS, developed in the 1990s, is used in clinical and research settings and actuarial assessment. The proposed AICIs for mortality are similar to the ICISS system for survival prediction with the advantage of the AICIs being predictive of 1-year survival as opposed to shorter term survival prediction with the use of ICISS. Both the CCI and AICIs were added to models including ICISS in the current study. It was found that the ICISS picked up most of the variability and so did age. Therefore, adding a comorbidity index to a model with ICISS may result only in a small additional increase in predictive power or adjustment of the ICISS score.

8.8 Effect of age on outcomes and comorbidities

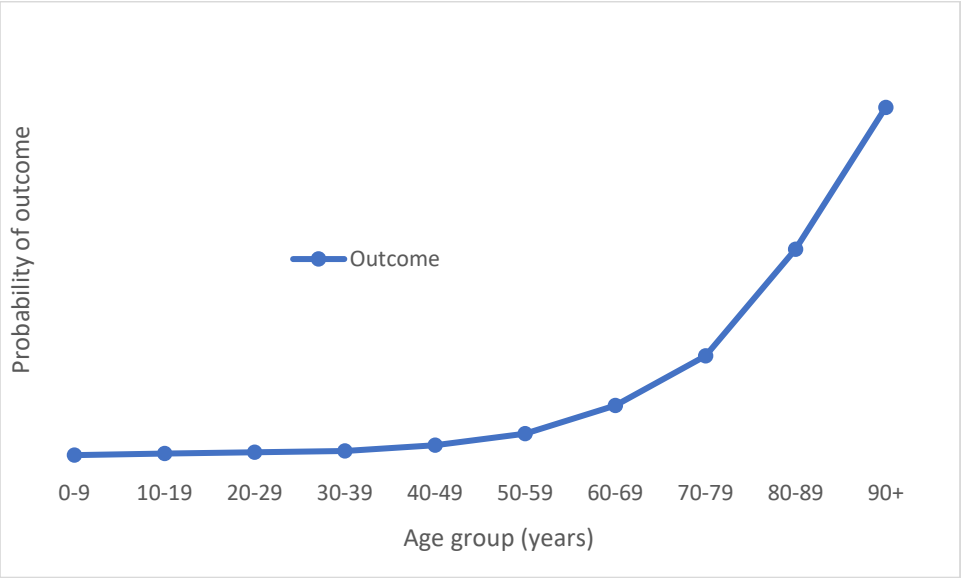
Past studies and this thesis showed that age is a key predictor of most injury outcomes. Therefore, it is important to discuss the dynamics of the age-outcome associations. There are two types of effects that age imposes on the results.

8.8.1 Non-linear effect of age on outcomes

The first is the non-linear effect of age on outcomes. The likelihood of an outcome starts to increase with age at a linear pace, but as patients reach the very oldest age groups, their vulnerability to various outcomes increase exponentially (Figure 5 (hypothetical example for illustration purpose only)). This is especially true for mortality and burden outcomes. For example, when an older person (more likely to be frail and weak) has a fall, recovery may take longer or they are more likely to succumb to the injury compared to a young adult (more likely to be physically fit and healthy). Given this exponential effect of age on certain outcomes, it indicates that a comorbidity index for this age group, especially when predicting injury outcomes, may

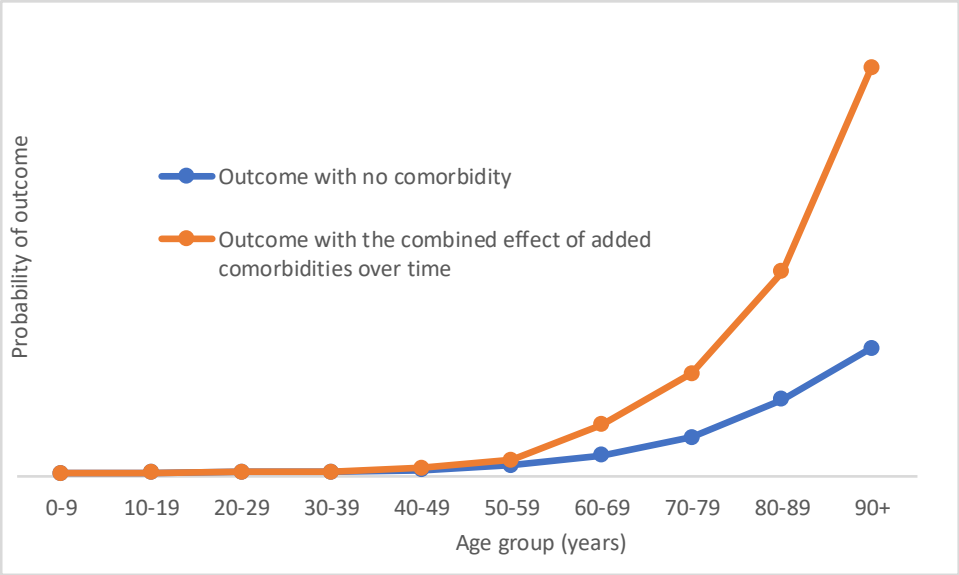
not be a very useful tool. This study demonstrated this with the comorbidity indices that were derived specifically for the 65+ years age group. It was seen that the age-specific indices for the older age groups did not significantly improve predictive power of regression models (paper attached to Chapter 4).

Figure 5: Non-linear effect of age on outcomes



The second is the age-specific effect of comorbidity on outcomes. The prevalence of chronic diseases increases with age. Therefore, there is a greater combined effect of comorbidities on outcomes in older populations (Figure 6 (hypothetical example for illustration purpose only)).

Figure 6: Age-specific effect of comorbidity on outcomes



This becomes more pronounced when the outcomes are followed up over a longer time, so the likelihood of comorbidity increases, thereby increasing the risk of the outcome. To address this, Charlson et al. (1987) [21] derived a composite index which allocates weights based on age-decades and comorbidity. This type of weighting is important for long-term outcomes (e.g., when patients are to be followed up for 10 years). However, the indices derived in the current study required a one-year or less follow up time, therefore did not require the indices to account for the effect of ageing.

8.9 Validations

A good index is robust to the dynamics of the populations it is applied to, i.e., it can be reliably used in various patient subgroups and different populations. This requires indices to be validated reasonably well among such groups. To this extent, the new AICIs and the frequently used CCI and ECM were validated in subgroups (based on demographics and injury characteristics) of the Victorian population. All

three indices were also validated externally in different populations (i.e., data from two other Australian states).

8.9.1 Internal validity

The AICIs for mortality validated well for children and patients with non-severe injury. Overnight stay- and cost-AICIs validated well for the over 65s, females, those with intracranial injury and patients with blunt trauma. Readmissions-AICIs validated well for children, males and patients with intracranial injury while complications-AICIs validated well for those with blunt and penetrating trauma. Overall, better validation was found for non-severe types of injuries and for those less than 65 years of age. Non-severe injury accounts for the larger proportion (87%) of injury patients. Therefore, these indices would appear to be best for adjusting for burden outcomes over mortality outcomes; mortality being more likely an outcome of serious injury. Given the observed variation in subgroup validation, caution and further investigation of other driving factors is recommended when using the AICIs in subpopulations. For example, AICIs' validation was poor for hip-fracture patients for almost all outcomes, which indicates the need to identifying other factors more pertinent to the outcomes for this group (e.g., surgical procedures and carer availability).

8.9.2 External validity

External validation is another method of confirming robustness of an index. To this extent, the new indices were validated using data from two other Australian states (NSW and WA). The Victorian and NSW populations are closer in size and profile, compared to the WA population. In the injury data used in this thesis, WA had a slightly different profile, having a lower proportion of older patients (>65 years of age), more males, and less serious injury than the other two states. Given that the indices still

validated well in WA, it can be said that the AICIs are robust for use in Australia to a reasonable extent. However, further validation in other states in addition to NSW and WA is recommended as coding differences exist across states. For example, Victoria records a statistically significantly higher number of codes per episode as 'complications' than the State of Queensland does [80].

Considerable variation in the proportion of records coded with condition onset flags (a data field indicating onset during admission) was found in the three states: 18% in Victoria, 8.5% in NSW and 10% in WA. This may have contributed to the complications-related comorbidity index's poor validation results in NSW (complication-identification was based on the condition onset flag for all states). This implies that it may not always be the demographic differences that influences the performance of these indices, but rather the capture of the relevant comorbidities or outcomes in the datasets used.

Apart from internal and external validations within a country, a robust index should work well in a global context. Therefore, international validations are also recommended prior to using the new indices outside Australia. Though the AICIs have a robustness similar to the CCI and ECM, the characteristics of a population outside Australia (e.g., one with a higher prevalence of HIV/AIDS) may render the AICIs (which excludes HIV/AIDS) inadequate for assessing mortality and burden over the CCI and ECM (both of which includes HIV/AIDS and was derived for these specific outcomes).

8.9.3 Generalisability

This thesis derived comorbidity indices for patients with *injury* as the index condition. Most indices currently available are for index *diseases* for general medical patient cohorts, and it has been nearly a decade since they have been updated; the

latest updates being the Quan 2011 update of CCI weights and the Walraven 2009 update of the ECM score to a point score [25, 81]. Potentially, the AICIs could be validated in general-medical patient cohorts as the indices are more up-to-date and outcome-specific than the CCI, ECM and their updates.

As was demonstrated in this thesis, the CCI and ECM which were derived using general-medical patient cohorts worked just as well as the injury-specific ones in most instances. The reverse may also hold true. But, the fact that the CCI, ECM and AICIs performed equally well in an *injury* cohort does not irrefutably demonstrate viability of the AICIs for all index *diseases;* therefore, this should be tested. For injury patients, it was shown that injury and age were the dominant features of outcome prediction, but for general patients, especially when certain index diseases are highly related to comorbidities, a validation of the new indices and comparison with the existing indices would be beneficial. The results may suggest that the AICIs are too parsimonious for index diseases. However, the AICIs may prove valuable in assessing hospital-acquired complications, which are likely to be reflect on hospital care more than on the index condition.

8.9.4 Validation of the CCI and ECM

The currency of the CCI and ECM is in question given they have been in use for more than two decades. These indices have been used frequently in past studies (as seen by the thousands of citations the Charlson and Elixhauser papers have received in the last couple of decades), some of which set out to validate the indices [25, 29, 47, 82] while others simply applied them as an adjustment for comorbidity. However, the validation of the CCI and ECM in the current study showed that the indices have aged well. The CCI has dated weights (although the updated CCI is less dated), and all three (CCI, updated CCI and ECM) include some conditions that are

irrelevant to current injury outcomes; yet, they mostly performed equally well as the more up-to-date and injury-specific indices derived in this thesis. This indicates that the CCI and ECM are relatively robust to time and index-conditions for outcome predictions. Nonetheless, the up-to-date, study population specific indices derived in this thesis are likely to be more useful (given their parsimony and relevance) beyond simple outcome prediction, such as in adjusting for the competing risks posed by comorbidity.

8.9.4.1 Dynamics of the AICIs, CCI and ECM

The previous section leads to the question regarding the dynamics of the AICIs, the CCI and the ECM. The conditions included in the AICIs are a combination of those in the CCI list (CCI list is almost the minimum list of the ECM and CCI, if the three conditions - cerebrovascular disease, dementia and myocardial infarction were ignored) and the ECM list (which is almost the maximum number of conditions from the CCI and ECM lists). The AICIs have been shown to be the most relevant and parsimonious of the three, but the conditions included are set by the boundaries of the CCI and ECM lists. Therefore, the similar predictive powers exhibited by all three indices could be mainly attributed to this. Hence, it is possible that the three indices are picking up the most relevant diseases for the outcomes they were originally intended for from the list of diseases available to each index at the time, with the AICIs including only the most relevant diseases (of the longer list) that reflect the association between the diseases and a broader spectrum of outcomes at the present time.

Should there be other populations likely to have higher prevalence of other diseases (not included in the 31 conditions chosen for this study), new indices that includes the extra diseases can be derived and compared with the AICI, CCI and ECM (as discussed in 8.3.2.2). If the AICIs, CCI and ECM still perform well, that would imply

that the conditions included in these three indices are very likely to be the comorbidities that are most likely to affect most outcomes, hence the limitation is addressed.

8.10 Limitations not discussed elsewhere

Limitations specific to each section, and some of the broader limitations were addressed in the previous chapters or in the papers/manuscripts attached to them. However, a few limitations which were not covered or elaborated on in the previous chapters will be discussed next.

8.10.1 Competing risks

A competing risk is an event that precludes or modifies the occurrence of the primary event of interest. In the current study, the index injury is the primary event and outcomes stemming from that injury are the primary outcomes of interest. Any subsequent injury during the follow up period or the development of a new comorbidity during this period poses a competing risk to the primary outcome; i.e., the new injury or the new comorbidity is able to influence the primary outcome. However, it was not possible to censor for these two competing risks occurring after the index injury in this study due to a lack of required data. Development and detection of a new chronic disease would require time, and would therefore most likely only affect outcomes which entail a longer follow-up (perhaps more than a year). They could also arise with complications, which was discussed in section 8.3.4. Conversely, new injuries (other than those occurring during the index hospital stay) could only effect outcomes post hospital-discharge, such as 30-day or 1-year mortality, and readmissions. In the context of the current study which uses only hospital admissions data, such new injuries outside the hospital would only be captured if they were also ultimately admitted to hospital. In that context, even if an attempt was made to include this

competing risk, it would not be a comprehensive capture since it only includes those admitted to hospital, which will result in an underestimate of the risk. Injuries occurring during the hospital stay on the other hand, can be captured with the data used in this study (CHADx complications). However, most of these injuries are likely to be outcomes of hospital care. These were mostly captured in the complications-related work that was already carried out in this thesis (Chapter 6). Therefore, given the shorter follow-up times of the outcomes assessed in this study, the non-adjustment for the two competing-risks discussed above is not expected to influence the results significantly.

8.10.2 Hospital admission-policy change

In the financial year 2012/13, a change was introduced to the Victorian hospital admission policy, such that patients who stayed for longer than four hours in the emergency department (who were considered a hospital admission prior to 2012/13) were no longer (post 2012/13) considered an 'admission'. This impacts the number of cases recorded as a hospital 'admission'; especially on the number of cases in cohort 2[6] of the current study. Though this affects the study population size, it is unlikely to affect the interval validity of the study, as the aim was to establish the associations between comorbidities and outcomes rather than focus on incidence or time trends. The cases lost to this change are likely the less-serious patients who would have had their entire stay (more than 4 hours) in the emergency department and sent home post 2012/13, without receiving an inpatient admission record.

[6] Cohort 2 dealt with 30-day and 1-year mortality for patients admitted between July 2006 and June 2015.

8.10.3 Methodological issues

There were methodological limitations of this thesis. Some of these were mentioned or discussed in detail in the previous chapters. This section includes methodological limitations that were mentioned in previous chapters but deserve further elaboration.

8.10.3.1 The large sample problem

The first is the problem of computing reliable statistics with large samples. Statistical tests are mostly designed for use with sample data and not population data [83], and the databases used in this thesis were population level. The inclusion of too many cases in a sample increases the analysis power which forces the rejection of the null hypothesis when the differences are actually negligible. The result: most statistical tests will return significant associations. This issue prevented the use of significance tests for assessing the relevance of various conditions in the current study; the problem was mentioned in the previous chapters (and the papers attached to them). It should be noted that if such tests were employed, for instance by selecting samples from the population data, a few more comorbidities may have been included or excluded from the new binary AICIs. That is, mainly those that were on the border line in terms of the AIC statistic difference of 10, which was used as the cut-off for inclusion into the models. However, this issue was overcome in the weighted AICIs, where effect sizes were employed to further eliminate comorbidities that did not have an effect size>=20%. Overall, it did not seem appropriate to select samples, as it was intended to ensure as much capture of comorbid conditions in this injury population as possible in order to derive comorbidity indices. Selecting subsets may have resulted in a lower capture of comorbidities and outcomes.

8.10.3.2 Thresholds for comorbidity weight calculations

The second issue was the threshold used for including conditions in the weighted comorbidity indices. These weights were calculated using the adjusted regression coefficients of comorbidities, when modelled against the outcome variables. That is, effect sizes - the size of the odds or risk that the outcome is possible for a patient with the comorbidity vs a patient without the comorbidity, were used. In the current study, an effect size >=20% was used as the threshold for a comorbidity to be included into the weighted model; the same threshold as used by the CCI. Lowering this threshold may have resulted in including more conditions and driven the weighted AICIs to perform as well as the binary AICIs. However, this is of little concern as the difference in predictive powers between the weighted and binary indices were small, and the conditions excluded due to this selection criteria were few. In the context of injury, a slight misspecification of the injury index through excluding lesser predictive factors from the weighting may not really make a substantial difference to the performance of either type of index as a whole.

Consideration was also given to using the lower/upper bounds of the regression coefficients rather than the actual coefficients (this was more for testing sensitivity in terms of comorbidity selection; however, they did not seem to substantially influence the selection of comorbidities since for most comorbidities the confidence limits were reasonably narrow). Choosing the lower bound did not change the inclusion capability of most comorbidities as the lower bounds were generally indicative of an effect size >=20%. Using the upper bounds would only change the value of the weights and therefore has no effect on the selection of the comorbidity to the index.

Using a weight that also combined comorbidity prevalence into the effect size was also considered (i.e., the weight is then based on the effect size as well as the

number of persons with the comorbidity). This then becomes very specific to this Victorian population and reduces the generalisability of the indices.

8.10.3.3 Comorbidity prevalence cut-off for inclusion in analysis

The third issue relates to the comorbidities selected for analysis in this thesis. Comorbidities were mainly selected using the algorithms (the algorithms are lists of ICD-10 codes for a selected list of conditions) used in the CCI and ECM according to published works by Quan et al.,(2005) [47]. To expand beyond these, comorbidities (or ICD-10 codes) were also identified that were frequently recorded in the study data but not listed in the CCI and ECM algorithms. However, a cut-off of >=1% prevalence was set in order for the condition to be considered for analysis for this additional measure. Using this methodology, the only additional conditions prevalent in greater than 1% of patients were likely to be *symptoms* or *complications* (e.g., dehydration, nausea/vomiting) rather than chronic diseases.

Apart from these, other ICD-10 codes related to chronic diseases that were not included in the Quan algorithm but with the highest prevalence below the 1% threshold were arthritis and osteoarthritis (0.5%) and osteoporosis (0.7%). Adding these conditions may have improved the new indices' performances in terms of model fit and predictive power over the CCI and ECM, though it cannot be confirmed if this would have been significant.

8.10.3.4 Lack of other predictor variables

There were data-related issues that may have contributed to poor performances of certain regression models in this thesis. In terms of predictor variables (other than comorbidity which was the main variable of interest), socio-demographic and injury-related variables were utilised. Apart from these, other

variables could also contribute to the performance of prediction-models. These were generally selected if they were considered to be reliably coded in datasets. For example, functional capacities related variables (such as FIM (Functional Independence Measure) score or Barthel Index) were not always populated in this data, therefore it was difficult to ascertain if all the relevant cases were actually coded; hence it was not used. Further, certain baseline variables that are likely to be associated with the outcomes were not collected in the hospital morbidity datasets, or were omitted at point of requesting the data from the data custodians. Most of these relate to hospital information such as hospital volume, treatment strategy, distance to hospital from injury occurrence location, hospital level (e.g., major trauma, metropolitan trauma or metropolitan primary care services) and facilities available at the hospital.

Other data-related aspects that could improve the performance of indices are: inclusion of the *severity* of comorbidities, better condition onset flag coding, and the inclusion of data on the cause of readmissions (specifically for indices related to readmissions).

Further, relationships between marital status and outcomes such as discharge destination and LOS is a generally expected association. Though this field was not included in the models for Victoria, they were included in WA. Adding this extra factor, improved the model fit in the WA data, but a significant improvement in predictive ability was not seen for any of the outcomes.

This thesis also lacked other baseline variables such as functional capacities of patients prior to injury (e.g., there could be a likelihood for longer LOS for patients with pre-existing functional impairment vs those without), and insurance status (e.g., shorter LOS for those without insurance vs those with public or private health cover).

These variables could affect some of the outcomes such as LOS and costs addressed in the study.

Finally, other baseline variables may exist which could improve outcome prediction. These could include information on past procedures patients may have undergone and current medications.

In summary, future improvements to the indices should overall attempt to improve the baseline models through inclusion of information on functional status, hospital information, comorbidity severity, cause for readmission, insurance status, past procedures and current medications.

8.10.3.5 Cost data

The comorbidity index derivation for costs in this thesis was solely based on cost-data from public hospitals. Whilst they are the substantial proportion of hospital costs in a jurisdiction, a picture of *total* costs could be obtained if cost data from private hospitals were also available. The more serious injuries are likely to be admitted to public hospitals while *some* of the less severe cases (which are the majority of admissions) could also be admitted to private hospitals. The costings of certain services in the private sector could also be higher than in the public sector, and if some of the services utilised by patients were due to comorbid conditions (e.g., diabetic patient will require blood glucose management during hospital stay, whereas a patient without will not require it), the costs are likely to increase and could affect the derivation of the cost-related comorbidity index. Therefore, the analysis related to costs may benefit from adding private-hospital costs and an adjustment for the type of hospital sector, in future research.

8.11 Use of the comorbidity indices in practice

8.11.1 Clinical vs statistical relevance

Clinical significance implies that the results are meaningful clinically, i.e., in real-life situations. A clinically meaningful result may not be detected if the statistical analysis power was low due to a small sample size [84]. Conversely, a result with limited clinical significance may be identified when statistical power is very high resulting from a large sample.

The conclusions drawn in this thesis are purely based on statistical analysis of retrospective data, except for the clinical input in identifying comorbidities for inclusion in models[7]. Conclusions are hence based on associations identified in the data which may not always make clinical sense. Therefore, all (new and existing) indices should always be used with reference to the context in which they were derived, and as a *supplement to* rather than as a *replacement for* clinical knowledge. Below is an explanation of how binary or weighted indices may not seem sensible in certain instances due to their summation effects. These are examples of how various comorbidity indices, their statistical significance and additive nature could distort the clinical relevance.

For example, consider two patients; patients A and B. Patient A has three comorbidities, C1, C2 and C3 which are non-life-threatening conditions. Patient B on

[7] The CCI and ECM lists were based on clinical consensus, and the choices this study made about excluding certain conditions prevalent in this study cohort were also based on a combination of statistical significance and clinical knowledge.

the other hand has one comorbidity (C4) which is life-threatening. Consider the outcome of mortality.

8.11.1.1 Disadvantage of weights

Given C1-C3 are non-life-threatening, in this example, a weighted index allocates a weight of 1 to each condition, and, C4, which is a life-threatening condition is allocated a weight of 3. Then performing simple arithmetic;

Patient A = C1(weight=1) + C2(weight=1) + C3(weight=1) = (summed weighted score=3) ➔ death (not likely as the conditions are not life-threatening)

Patient B = C4 (weight=3)➔death (likely)

Likelihood of mortality is scored equally for both patients even though clinically it is known that Patient B is more likely to die. This suggests that a *maximum* of weights amongst the conditions present might be a better measure than a *sum* of weights.

8.11.1.2 Disadvantage of binary representation

In this example there is no weight, but the binary representation allocates either a “1” or “0” depending on the presence of the condition, which in turn does “behave” like a weight.

Patient A = C1(1) + C2(1) + C3(1) = (summed score=3) ➔ death (not likely as the conditions are not life-threatening)

Patient B = C4 (1)➔ no death (whereas in fact death is likely because it is a life-threatening condition)

Likelihood of mortality is scored greater for Patient A even though clinically it is known that Patient B is more likely to die.

The above example shows that summation leads to potentially incorrect predictions for individual patients. However, this is balanced by the fact that the predictive power of the models in this study was close, suggesting that, whilst there might be problems in predicting outcomes for an individual, overall the representations are quite close and do not lead to gross errors across the population.

The potential bias in different types of scores towards an outcome imply that they should be used with caution, especially if used in clinical settings to predict outcomes for individual patients. That is, in clinical settings, clinical input (a Delphi method for instance) to the indices could potentially provide better insights than a purely statistically-derived comorbidity score. Further, adding a factor for the comorbidities' cogency (e.g., life threatening nature of the condition) into the weights could aid in adjusting for this summation effect in individual cases.

8.11.2 Advantages of the AICIs in practical use over the CCI and ECM

The two main advantages of the AICIs over the CCI and ECM are parsimony and relevance to the outcomes of interest. The AICIs as discussed in previous chapters are less resource intensive than the ECM. They use less conditions, making them even more versatile in settings where information on the presence of comorbidities requires data collection (i.e., they are not readily available). Nevertheless, in administrative data this is less of an issue since information on most comorbidities is collected routinely. Further, some AICIs have a smaller number of conditions than the CCI (CCI being more parsimonious than the ECM), making those AICIs versatile even over the CCI.

Another advantage (though not as notable as the former two) of the AICIs over the CCI and ECM is the lower number of false negatives. Relative differences in overall

predictive power between the AICIs, CCI and ECM, was small, with predictive power being mainly determined by the baseline factors, as explained in the previous chapter. However, it was seen that there were some gains in using the AICIs over the CCI in terms of false negative *numbers*, though the same cannot be stated with *rates* as there were no statistically significant differences in rates. The *number* of erroneously classified cases (deaths for instance) with the use of the AICIs were lower than with the use of the CCI. The insignificant differences in *rates* imply that the two indices are not vastly different in classifying patients, but the lower *number* of patients erroneously classified when using the AICIs could be of value in clinical settings, where individual patient numbers matter.

In clinical settings, it would be important to consider every life that could be misclassified; that is minimise the number of erroneously classified patients. For example, the index classifies a patient as in no danger of mortality and gets discharged from hospital when there is a chance of mortality in the coming days. In that sense, the index that is likely to provide the least 'number' of incorrect classifications would be the recommended index. For most outcomes in the current study, the Elixhauser index came out best followed by the newly derived indices, followed by the frequently used Charlson index in this aspect. However tedious it might be to use the Elixhauser index (given it has the longest list of comorbidities to account for and check presence for), it would still be a better choice that the latter two. In research settings however, these indices are used with large cohorts of patients and the 'proportions' misclassified would suffice in determining the usefulness of an index. At this point, if one is reliant on an administrative database, the capture of comorbidities using a longer list such as the Elixhauser is not cumbersome, as they can be easily extracted. If one were to use

medical chart reviews or other means including patient recollection, it might serve useful to limit the conditions to those recommended in our new indices.

8.11.3 Application of comorbidity indices

Comorbidity indices could fulfil various objectives. In triage settings, when patient-care plans and risk classification assessments are necessary, these indices can be used for adjusting for comorbidities when they are competing risks (provided the injury severity and age do not dominate the outcome). Other potential utilities are in evaluating and comparing treatments, and identifying comorbidities relevant to an outcome.

8.12 The importance of this research

The frequent use of the popular CCI in past research was the motivation for this thesis to test its validity among injury patients. The CCI was not derived for injury patients, contains conditions clinically irrelevant in present contexts, and was not derived for specific outcomes, except for 1-year mortality. This thesis, however, showed that the CCI does work well both in an injury context and outcomes other than 1-year mortality, while it also showed the CCI's limits. In the event this study was not conducted, the CCI's appropriateness in injury and specific-outcome settings would still remain minimally validated, and also the justifiability of the injury-related studies of the 29,000 plus citations of the Charlson et al. (1987) paper would remain in question.

The thesis also raised the question of how frequent the review of comorbidity indices should take place. The CCI and ECM performed as well as the current AICIs, even though the former two are many decades older. Therefore, the AICIs could also be expected to age well, given the similar performance capacities. The exception will

be when chronic disease prevalence changes substantially. Prevalence of a disease could increase or decrease over time. For example, the prevalence of peptic ulcer disease would be less now than when the CCI was developed as the condition now has better treatment options, and therefore does not remain a chronic disease. However, with low prevalence, the disease will have little effect on the CCI and ECM, making the two indices more parsimonious and causing them to behave more like most AICIs for peptic ulcer.

Therefore, a (dramatic) increase in prevalence could determine whether the indices need a review. The present study did not look at temporal trends in injury and comorbidity; therefore, the performance of the three indices across time was not assessed using data from this study. Overall, this thesis has shown that comorbidity indices may not require updating often, but should be reviewed at least every decade to ensure they remain applicable.

8.13 Future research

8.13.1 Researching other outcomes

This thesis assessed the association between comorbidity and outcomes of hospital admitted injury patients; outcomes in relation to mortality, burden and complications, the latter two representing a burden on both patients and hospitals. Apart from these, comorbidity may play a more significant role in outcomes such as functional status - which represents an ability to perform daily activities of living. For instance, a patient with musculoskeletal conditions who has a fall, may likely find that recovery takes much longer and require more support. If other data sources apart from hospital data are used, there may be a possibility of assessing the associations

between other functionality-related outcomes such as recovery-time post discharge or time to return to work, and comorbidities.

8.13.2 Other options for derivation and validation

This project derived a suite of comorbidity indices based on an analysis of retrospective administrative data. It is recommended that in the future, these new indices should be validated using data from medical chart review. Further, *new* indices could also be derived using such data. Both these (validation and derivation using chart data) will assist in establishing if administrative data is sufficient or chart review can improve the capture of the association between comorbidities and outcomes.

Another potential focus is to validate the indices in a prospective study. Outcome prediction tools are now being widely researched, and industry giants such as Google and IBM are already in the process of establishing such tools using artificial intelligence. In populations with a high prevalence of comorbidities, and to outcomes where comorbidities are highly relevant (such as LOS and costs over readmission and mortality), prospective prediction tools will be of value. They could be tailored for use especially in clinical settings. The tool would not be intended to replace clinical knowledge, but could be used for assisting clinical decisions. This could be highly relevant at point of hospital admission for risk-stratifying patients and allocating resources. Finally, they will also be useful in care settings when the possibility of a patient's health deteriorating can be predicted.

8.13.3 Next steps for usage of comorbidity indices

Derivation and validation of comorbidity indices are important, but the end-goal is the appropriate use after their development. As discussed in previous sections, the performance ability of an index varies with the study population and outcome.

As an extension to this project, the compilation of a user manual for comorbidity indices is recommended. This would include a guide to choices of appropriate indices, recommendations of when, where and why each should be used, and adaptations that should be considered.

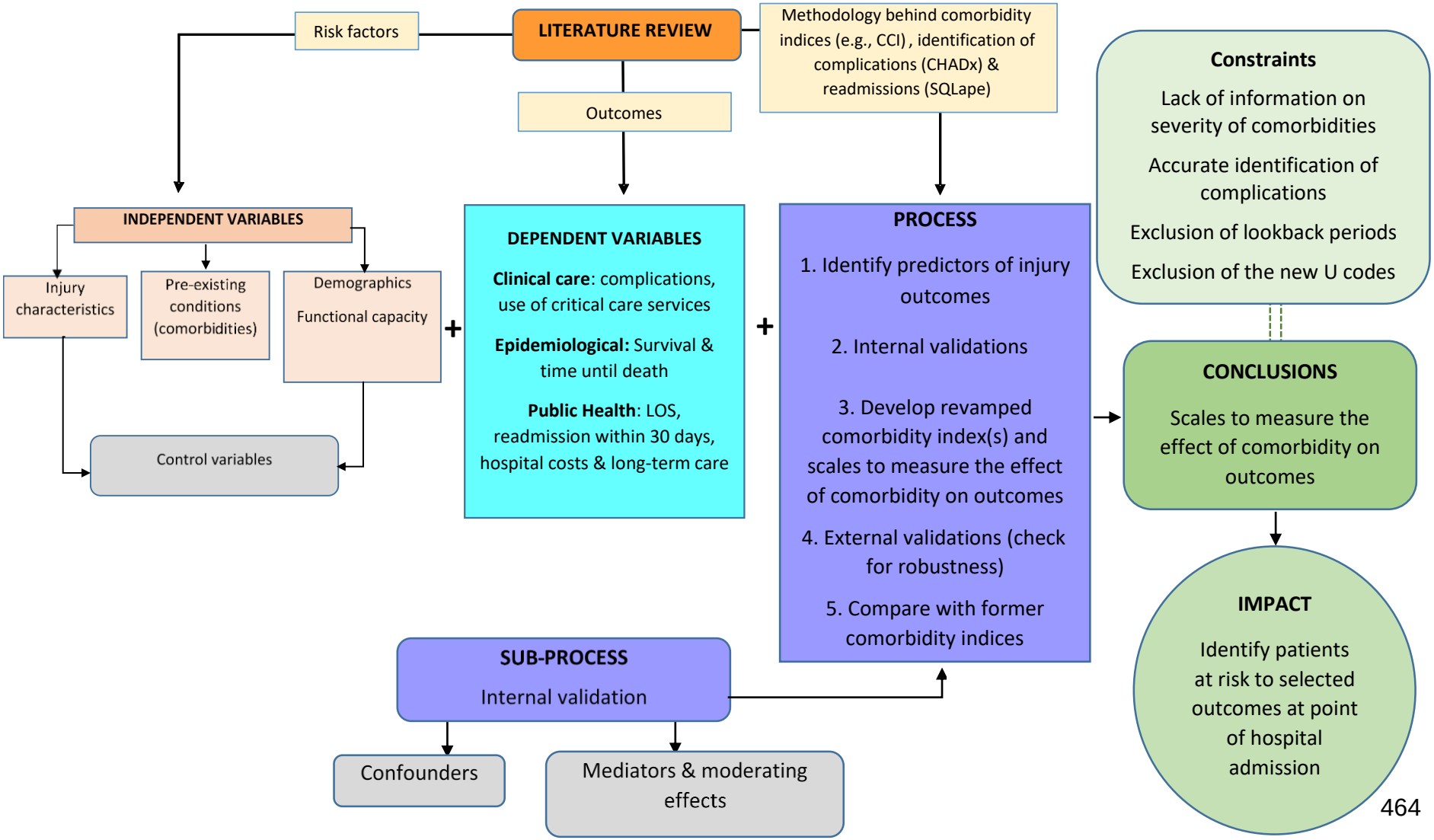
8.13.4 Relevance in the future

The current demographic trend is towards an ageing population with increased likelihood of chronic diseases (includes conditions such as obesity). Older cohorts are also likely to have more injuries related to events such as burns and falls. Furthermore, there is a trend for older persons to remain in their own home for longer, whereas in the past they moved to residential care facilities at an earlier age. Living on their own makes older persons more susceptible to injury. They are also likely to have more chronic diseases (arthritis for instance) than their younger counterparts, and therefore prone to more serious outcomes such as hip-fractures should they have a fall.

Apart from these, changes in lifestyle (inactivity, smoking etc.), including changes in occupational hazards, all contribute to a change in injury epidemiology and susceptibility to chronic diseases. On the positive side of life-style changes, increased physical activity for health reasons, healthy eating habits etc. can contribute to a reduction in injury and chronic disease. However, extra physical activity also increases chances of injury and could add to the injury burden. In this context, establishing the correct associations between a population's characteristics, comorbidities and outcomes are important in the management of injury patients in the future, planning of health and social service resources, and assessing risk for actuarial purposes. To that extent, robust comorbidity indices are likely to become increasingly relevant for injury patients.

9 Appendices

Appendix 1: Methodological framework for the injury comorbidity index study



Appendix 2: ICD-10 codes used to identify comorbidity groups

The following is a list of the 34 comorbidity groups identified in the CCI and ECM algorithms according to Quan et al. [47] and Sundararajan et al. [48].

Comorbidity group	ICD-10 code
HIV/AIDS	B20-B24
Alcohol dependence	F10, E52, G62.1, I42.6, K29.2, K70.0, K70.3, K70.9, T51.x, Z50.2, Z71.4, Z72.1
Drug dependence	F11.x-F16.x, F18.x, F19.x, Z71.5, Z72.2
Any malignancy	C00.x-C26.x, C30.x-C34.x, C37.x- C41.x, C43.x, C45.x-C58.x, C60.x- C76.x, C80, C81.x-C85.x, C88.x, C90.x-C97.x
Blood loss anaemia	D50.0
Cardiac arrhythmias	I44.1-I44.3, I45.6, I45.9, I47.x-I49.x, R00.0, R00.1, R00.8, T82.1, Z45.0, Z95.0
Cerebrovascular disease	G45.x, G46.x, H34.0, I60.x-I69.x
Chronic pulmonary disease	I27.8, I27.9, J40.x-J47.x, J60.x-J67.x, J68.4, J70.1, J70.3
Coagulopathy	D65-D68.x, D69.1, D69.3- D69.6
Congestive heart failure	I09.9, I11.0, I13.0, I13.2, I25.5, I42.0, I42.5-I42.9, I43.x, I50.x, P29.0
Deficiency anaemias	D50.8, D50.9, D51.x-D53.x
Dementia	F00.x-F03.x, F05.1, G30.x, G31.1

Depression	F20.4, F31.3-F31.5, F32.x, F33.x, F34.1, F41.2, F43.2
Diabetes with chronic complications	E10.2-E10.5, E10.7, E11.2-E11.5, E11.7, E12.2-E12.5, E12.7, E13.2- E13.5, E13.7, E14.2-E14.5, E14.7
Diabetes without complications	E10.0, E10.1, E10.6, E10.8, E10.9, E11.0, E11.1, E11.6, E11.8, E11.9, E12.0, E12.1, E12.6, E12.8, E12.9, E13.0, E13.1, E13.6, E13.8, E13.9, E14.0, E14.1, E14.6, E14.8, E14.9
Fluid and electrolyte disorders	E22.2, E86.x, E87.x
Hemiplegia/paraplegia	G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0-G83.4, G83.9
Hypertension complicated	I10.x
Hypertension uncomplicated	I11.x-I13.x, I15.x
Hypothyroidism	E00.x-E03.x, E89.0
Metastatic solid tumor	C77.x-C80.x
Mild liver disease	B18.x, K70.0-K70.3, K70.9, K71.3-K71.5, K71.7, K73.x, K74.x, K76.0, K76.2-K76.4, K76.8, K76.9, Z94.4
Moderate or severe liver disease	I85.0, I85.9, I86.4, I98.2, K70.4, K71.1, K72.1, K72.9, K76.5, K76.6, K76.7
Myocardial infarction	I21.x, I22.x, 125.2
Obesity	E66.x

Other neurological disorders	G10.x-G13.x, G20.x- G22.x, G25.4, G25.5, G31.2, G31.8, G31.9, G32.x, G35.x-G37.x, G40.x, G41.x, G93.1, G93.4, R47.0, R56.x
Peptic ulcer disease	K25.x-K28.x
Peripheral vascular disease	I70.x, I71.x, I73.1, I73.8, I73.9, 177.1, 179.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9, R02
Psychoses	F20.x, F22.x-F25.x, F28.x, F29.x, F30.2, F31.2, F31.5
Pulmonary circulation disorders	I26.x, 127.x, I28.0, I128.8, 128.9
Renal disease including renal failure	I12.0, I13.1, N01, N03, N05.2- N05.7, N072, N073, N074, N18.x, N19.x, N25.0, Z49.0- Z49.2, Z94.0, Z99.2
Rheumatic disease including some other connective tissue disorders	L94.0, L94.1, L94.3, M05.x, M06.x, M08.x, M12.0, M12.3, M30.x, M31.0- M31.3, M32.x-M35.x, M45.x, M46.1, M46.8, M46.9, M31.5, M36.0
Valvular disease	A52.0, I05.x-I08.x, I09.1, I09.8, I34.x-I39.x, Q23.0-Q23.3, Z95.2- Z95.4
Weight loss	E40.x-E46.x, R63.4, R64

Appendix 3: Ethics approvals

MONASH University

Monash University Human Research Ethics Committee

Approval Certificate

This is to certify that the project below was considered by the Monash University Human Research Ethics Committee. The Committee was satisfied that the proposal meets the requirements of the *National Statement on Ethical Conduct in Human Research* and has granted approval.

Project Number:	1256
Project Title:	The injury comorbidity index study
Chief Investigator:	Dr Janneke Berecki-Gisolf
Expiry Date:	04/11/2021

Terms of approval - failure to comply with the terms below is in breach of your approval and the *Australian Code for the Responsible Conduct of Research*.

1. The Chief Investigator is responsible for ensuring that permission letters are obtained, if relevant, before any data can occur at the specified organisation.
2. Approval is only valid whilst your hold a position at Monash University.
3. It is responsibility of the Chief Investigator to ensure that all investigators are aware of the terms of approval and to ensure the project is conducted as approved by MUHREC.
4. You should notify MUHREC immediately of any serious or unexpected adverse effects on participants or unforeseen events affecting the ethical acceptability of the project.
5. The Explanatory Statement must be on Monash letterhead and the Monash University complaints clause must include your project number.
6. Amendments to approved projects including changes to personnel must not commence without written approval from MHUREC.
7. Annual Report - continued approval of this project is dependent on the submission of an Annual Report.
8. Final Report - should be provided at the conclusion of the project. MUHREC should be notified if the project is discontinued before the expected completion date.
9. Monitoring - project may be subject to an audit or any other form of monitoring by MUHREC at any time.
10. Retention and storage of data - The Chief Investigator is responsible fo the storage and retention of the original data pertaining to the project for a minimum period of five years.

Thank you for your assistance.

Professor Nip Thomson

Chair, MUHREC

Page 1 of 1

Working together to lessen the impact of cancer

14 August 2017

Dr Janneke Berecki-Gisolf
Monash University Accident Research Centre
21 Alliance Lane
Clayton VIC 3800

Dear Dr Berecki-Gisolf,

NSW Population & Health Services Research Ethics Committee

AU RED Reference: HREC/17/CIPHS/16

Cancer Institute NSW Reference: 2017/HRE0601

Project Title: The injury comorbidity index study

Thank you for your correspondence dated 13 July 2017 responding to a request for further information/clarification of the above referenced study, submitted to the NSW Population & Health Services Research Ethics Committee. The Committee has reviewed your response and has agreed that the aforementioned application meets the requirements of the *National Statement on Ethical Conduct in Human Research (2007)*. This approval is for a maximum of five years from the date of this letter, after which time a renewal application will be required if the protocol has not been completed.

The Committee granted a waiver of the usual requirement of consent for the use of re-identifiable information held by NSW agencies, in line with the State Privacy Commissioner's Guidelines for Research and the Health Records and Information Privacy Act 2002 (NSW).

The documents reviewed and approved include:

- Letter of Response, dated 13 July 2017
- Cover Letter, dated 17 May 2017
- NSW National Ethics Application Form, v2.2, submission code AU/1/FDDD219, dated 16 May 2017
- Protocol version 2, dated 4 August 2017
- Data Linkage Flowchart
- CHeReL Technical Feasibility Letter, dated 2 February 2017
- CHeReL Application for Data
- Updated NSW APDC Data Variable Checklist, submitted via email on 13 July 2017
- NSW APDC Data Custodian Sign Off Form, dated 8 May 2017
- NSW RBDM Data Variable Checklist
- NSW COD-URF Data Variable Checklist
- NSW RBDM & COD-URF Data Custodian Sign Off Form, dated 3 February 2017
- NSW Privacy Form
- Monash University HREC Certificate of Approval
- IDC10 Code List
- Peer Review Report, dated 4 August 2017

Cancer Institute NSW
ABN 48 538 442 594
Level 9, 8 Central Avenue, Australian Technology Park, Eveleigh NSW 2015
PO Box 41, Alexandria, NSW 1435
t +61 (0)2 8374 5600 f +61 (0)2 8374 3600 e information@cancerinstitute.org.au
www.cancerinstitute.org.au

Approval is now valid for the following sites:

- Monash University Accident Research Centre, Monash University VIC

The NSW Population & Health Services Research Ethics Committee has been accredited by the NSW Ministry of Health to provide single ethical and scientific review of research proposals conducted within the NSW public health system.

The Committee is a joint initiative of the Cancer Institute NSW and NSW Ministry of Health. The Committee has been constituted and operates in accordance with the National Health and Medical Research Council's *National Statement on Ethical Conduct in Human Research (2007)* and relevant legislation and guidelines.

Please note that ethical approval is valid for **5 years**, conditional on the following:

- Principal investigators will immediately report anything which might warrant a review of ethical approval of the research, including unforeseen events that might affect continued ethical acceptability.
- Proposed amendments to the research proposal or conduct of the research which may affect the ethical acceptability of the research are to be provided to the NSW Population & Health Services Research Ethics Committee for review.
- The NSW Population & Health Services Research Ethics Committee will be notified giving reasons, if the research is discontinued before the expected date of completion.
- The Principal Investigator will provide a progress report to the NSW Population & Health Services Research Ethics Committee annually and at the completion of the study.

Your first progress report will be due on **14/08/2018** and the duration of approval is until **14/08/2022**, after which time a new submission to the Ethics Committee will be required.

You are reminded that this letter constitutes *'ethical approval'* only. This research project must not commence at a site until separate authorisation from the Chief Executive or delegate of that site has been obtained. It is your responsibility to forward a copy of this letter together with any approved documents as enumerated above, to all site investigators for submission to the site's Research Governance Officer. Where relevant, copies will also need to be provided to the CHeReL and the data custodian.

For further information about the NSW Population & Health Services Research Ethics Committee, please refer to our website https://www.cancerinstitute.org.au/Data-research/Research-ethics-committee.

Should you have any queries about the ethical review of your research proposal, please contact ethics at ethics@cancerinstitute.org.au.

Yours sincerely,

Professor David Roder
Chairperson, NSW Population & Health Services Research Ethics Committee

Government of **Western Australia**
Department of **Health**

DOH WA Human Research Ethics Committee
Level 1, C Block
189 Royal Street
EAST PERTH WA 6060

12 October 2017

Dr Janneke Berecki-Gisolf
Director
Victorian Injury Surveillance Unit
Monash University Accident Research Centre
21 Alliance Lane
Clayton VICTORIA 3800

Dear Dr Berecki-Gisolf

PRN: RGS0000000613
Project Title: The Injury Comorbidity Index Study

Thank you for submitting the above research project for ethical review. This project was considered by the Department of Health WA Human Research Ethics Committee at its meeting held on 11 October 2017.

I am pleased to advise you that the DOH HREC has granted ethical approval of this research project.

The nominated participating site(s) in this project is/are:

Department of Health

[Note: If additional sites are recruited prior to the commencement of, or during the research project, the Coordinating Principal Investigator is required to notify the Human Research Ethics Committee (HREC). Notification of withdrawn sites should also be provided to the HREC in a timely fashion.]

The approved documents include:

Document	Version	Version Date
Attachment_1256 Certificate of Approval_version1.pdf	1	04/11//2016
2017 HRE0601 - Ethics approval from NSW PHSREC_version1.pdf	1	14/08/2017
Peer-Review-Report_ICIS project_version1.pdf	1	04/08/2017
Attachment_ICIS project Research Protocol-	1	14/09/2017

Government of **Western Australia**
Department of **Health**

Version 1_14.09.2017.docx		
201706.04_Feasibility_letter.pdf	1	08/09/2017
02_201706.04_Extraction_Final.doc	1	06/09/2017
03a_201706.04_Hospital_Morbidity_Final.doc	1	06/09/2017
04b_201706.04_Mortality_Final.doc	1	06/09/2017
Attachment_201706.04_data_flow.pptx	1	06/09/2017
Attachment_ICIS project Data Linkage Flow Chart-Version 1_17.05.2017.xlsx	1	17/05/2017
01_201706.04_Application for Data_Final.pdf	1	06/09/2017
Ethics Investigator Response Letter_ICIS project_version 1.pdf	1	13/10/2017

Ethical approval of this project from DOH HREC is valid from 11 October 2017 to 11 October 2020 subject to compliance with the 'Conditions of Ethics Approval for a Research Project' (Appendix A).

A copy of this ethical approval letter must be submitted by all site Principal Investigators to the Research Governance Office or equivalent body or individual at each participating institution in a timely manner to enable the institution to authorise the commencement of the project at its site/s.

This letter constitutes ethical approval only. This project cannot proceed at any site until separate site authorisation has been obtained from the Chief Executive or Delegate of the site under whose auspices the research will be conducted at that site.

Should you have any queries about the DOH HREC's consideration of your project, please contact the Ethics Office at hrec@health.wa.gov.au or on 08 9222 4278. The HREC's Terms of Reference, Standard Operating Procedures and membership are available from the Ethics Office or from http://www.health.wa.gov.au/healthdata/hrec/.

The HREC wishes you every success in your research.

Yours sincerely

Dr Peter Bentley MBBS MBA
Chair
Department of Health WA Human Research Ethics Committee

Clinical Senior Lecturer
School of Medicine and Pharmacology &
School of Pathology and Laboratory Medicine, UWA

Appendix A

CONDITIONS OF ETHICS APPROVAL FOR A RESEARCH PROJECT

The following general conditions apply to the research project approved by the Human Research Ethics Committee (HREC) and acceptance of ethical approval will be deemed to be an acceptance of these conditions by all project investigators:

1. The responsibility for the conduct of this project lies with the Coordinating Principal Investigator (CPI).
2. The investigators recognise the reviewing HREC is registered with the National Health and Medical Research Council and that it complies with the current version of the National Statement on Ethical Conduct in Human Research.
3. A list of HREC member attendance at a specific meeting is available on request, but no voting records will be provided.
4. The CPI will immediately report anything that might warrant review of ethical approval of the project.
5. The CPI will notify the HREC of any event that requires a modification to the protocol or other project documents and submit any required amendments to approved documents, or any new documents, for ethics approval. Amendments cannot be implemented at any participating site until ethics approval is given.
6. The CPI will submit any necessary reports related to the safety of research participants in accordance with the WA Health Research Governance Standard Operating Procedures.
7. Where a project requires a Data Safety Monitoring Board (DSMB), the CPI's will ensure this is in place before the commencement of the project and notify the HREC. All relevant reports from the DSMB should be submitted to HREC.
8. For investigator-initiated and collaborative research group projects the CPI may take on the role of the sponsor. In this case, the CPI is responsible for reporting to the Therapeutic Goods Administration (TGA) any unexpected serious drug or device adverse reactions, and significant safety issues in accordance with the TGA guidelines.
9. If the project involves the use of an implantable device, the CPI will ensure a properly monitored and up to date system for tracking participants is maintained for the life of the device.
10. The CPI will submit a progress report to the HREC annually from the ethics approval date and notify the HREC when the project is completed at all sites. The HREC can request additional reporting requirements as a special condition of a research project. Ethics approvals are subject to the receipt of these reports and approval may be suspended if the report is not received.
11. The CPI will notify the HREC of his or her inability to continue as CPI and will provide the name and contact information of their replacement. Failure

to notify the HREC can result approval for the project being suspended or withdrawn.

12. The CPI will notify the HREC of any changes in investigators and/or new sites that will utilise the ethics approval.
13. The HREC has the authority to audit the conduct of any project without notice if some irregularity has occurred, a complaint is received from a third party or the HREC decides to undertake an audit for quality improvement purposes.
14. The HREC may conduct random monitoring of any project. The CPI will be notified if their project has been selected. The CPI will be given a copy of the monitor's report along with the HREC and Research Governance (RG) Office at the site/s.
15. Complaints relating to the conduct of a project should be directed to the HREC Chair and will be promptly investigated according to the WA Health's complaints procedures.
16. The CPI should ensure participant information and consent forms are stored within the participant's medical record in accordance with the WA Health's RecordKeeping Plan.
17. The CPI will notify the HREC of any plan to extend the duration of the project past the expiry date listed above and will submit any associated required documentation. A request for an extension should be submitted prior to the expiry date. One extension of 5 years may be granted but approval beyond this time period may necessitate further review by the HREC.
18. Once the approval period has expired or the project is closed, the CPI will submit a final report. If the report is not received within 30 days the project will be closed and archived.
19. Projects that do not commence within 12 months of the approval date may have their approval withdrawn and the project closed. The CPI must outline why the project approval should remain.
20. The CPI will notify the HREC if the project is temporarily halted or prematurely terminated at a participating site before the expected completion date, with reasons provided. Such notification should include information as to what procedures are in place to safeguard participants.
21. If a project fails to meet these conditions the HREC will contact the CPI to address the identified issues. If, after being contacted by the HREC, the issues are not addressed, the ethics approval will be withdrawn. The HREC will notify the RG Office at each site within WA Health that the project procedures must discontinue, except for those directly related to participant's safety.

10 References

1. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **Effect of comorbidity on injury outcomes: a review of existing indices**. *Ann Epidemiol* 2019, **36**:5-14.
2. World Health Organization. **The global burden of disease: 2004 update**. Switzerland: WHO; 2008.
3. Haagsma JA, Graetz N, Bolliger I, Naghavi M, Higashi H, Mullany EC, Abera SF, Abraham JP, Adofo K, Alsharif U *et al*. **The global burden of injury: incidence, mortality, disability-adjusted life years and time trends from the Global Burden of Disease study 2013**. *Inj Prev* 2016, **22**(1):3-18.
4. **Global health estimates 2014 summary tables.** http://www.who.int/healthinfo/global_burden_disease/en/. Accessed 04th November 2019.
5. Australian Bureau of Statistics. **Causes of Death, Australia**. *Catalogue 33030.* Canberra: ABS; 2018.
6. Australian Institute of Health and Welfare. **Trends in hospitalised injury, Australia 2007–08 to 2016–17**. Canberra: AIHW; 2019.
7. Baker SP, O'Neill B, Karpf RS. **The Injury fact book**, 2nd edn. New York: Oxford University Press; 1992.
8. **Medical Definition of Chronic Disease** http://www.medicinenet.com/script/main/art.asp?articlekey=33490. Accessed 23 August 2017.
9. **The NSW health outcomes program.** http://www.publish.csiro.au/NB/pdf/NB92067. Accessed 06th November 2019.
10. Feinstein AR. **The pre-therapeutic classification of co-morbidity in chronic disease**. *J Chronic Dis* 1970, **23**(7):455-468.
11. Charlson ME, Wells MT, Kanna B, Dunn V, Michelen W. **Medicaid managed care: how to target efforts to reduce costs**. *BMC Health Serv Res* 2014, **14**(1):1-8.
12. Mitchell RJ, Cameron CM, McClure R. **Higher mortality risk among injured individuals in a population-based matched cohort study**. *BMC Public Health* 2017, **17**:150.
13. Cameron CM, Purdie DM, Kliewer EV, McClure RJ. **Differences in prevalence of pre-existing morbidity between injured and non-injured populations**. *Bull World Health Organ.* vol. 83; 2005: 345+.
14. Valderas JM, Starfield B, Sibbald B, Salisbury C, Roland M. **Defining comorbidity: implications for understanding health and health services**. *The Annals of Family Medicine* 2009, **7**(4):357-363.

15. Thompson H, Dikmen S., Temkin N. **Prevalence of Comorbidity and its Association with Traumatic Brain Injury and Outcomes in Older Adults**. *Res Gerontol Nurs* 2012, **5**(1):17-24.

16. Ahmad R, Cherry RA, Lendel I, et al. **Increased hospital morbidity among trauma patients with diabetes mellitus compared with age- and injury severity score–matched control subjects**. *Arch Surg* 2007, **142**(7):613-618.

17. van Walraven C, Dhalla IA, Bell C, Etchells E, Stiell IG, Zarnke K, Austin PC, Forster AJ. **Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community**. *Can Med Assoc J* 2010, **182**(6):551-557.

18. Gabbe BJ, Harrison JE, Lyons RA, Edwards ER, Cameron PA. **Comparison of measures of comorbidity for predicting disability 12-months post-injury**. *BMC Health Serv Res* 2013, **13**(1):1.

19. Lustenberger T, Talving P, Lam L, Inaba K, Bass M, Plurad D, Demetriades D. **Effect of diabetes mellitus on outcome in patients with traumatic brain injury: a national trauma databank analysis**. *Brain Inj* 2013, **27**(3):281-285.

20. Kaplan MH, Feinstein AR. **The importance of classifying initial co-morbidity in evaluating the outcome of diabetes mellitus**. *J Chronic Dis* 1974, **27**(7):387-404.

21. Charlson ME, Pompei P, Ales KL, MacKenzie CR. **A new method of classifying prognostic comorbidity in longitudinal studies: development and validation**. *J Chronic Dis* 1987, **40**(5):373-383.

22. Elixhauser A, Steiner C, Harris DR, Coffey RM. **Comorbidity measures for use with administrative data**. *Med Care* 1998, **36**(1):8-27.

23. Von Korff M, Wagner EH, Saunders K. **A chronic disease score from automated pharmacy data**. *J Clin Epidemiol* 1992, **45**(2):197-203.

24. Fishman AP, Shay KD. **Development and estimation of a pediatric chronic disease score using automated pharmacy data**. *Med Care* 1999, **37**(9):874-883.

25. Quan H, Li B, Couris CM, Fushimi K, Graham P, Hider P, Januel J-M, Sundararajan V. **Updating and validating the Charlson comorbidity index and score for risk adjustment in hospital discharge abstracts using data from 6 countries**. *Am J Epidemiol* 2011, **173**(6):676-682.

26. Holman CAJ, Preen DB, Baynham NJ, Finn JC, Semmens JB. **A multipurpose comorbidity scoring system performed better than the Charlson index**. *J Clin Epidemiol* 2005, **58**(10):1006-1014.

27. Ghali WA, Hall RE, Rosen AK, Ash AS, Moskowitz MA. **Searching for an improved clinical comorbidity index for use with ICD-9-CM administrative data**. *J Clin Epidemiol* 1996, **49**(3):273-278.

28. Klabunde CN, Potosky AL, Legler JM, Warren JL. **Development of a comorbidity index using physician claims data**. *J Clin Epidemiol* 2000, **53**(12):1258-1267.

29. Martins M, Blais R. **Evaluation of comorbidity indices for inpatient mortality prediction models**. *J Clin Epidemiol* 2006, **59**(7):665-669.

30. Schneeweiss S, Wang PS, Avorn J, Glynn RJ. **Improved comorbidity adjustment for predicting mortality in Medicare populations**. *Health Serv Res* 2003, **38**(4):1103-1120.

31. Thompson HJ, Rivara FP, Nathens A, Wang J, Jurkovich GJ, Mackenzie EJ. **Development and Validation of the Mortality Risk for Trauma Comorbidity Index**. *Ann Surg* 2010, **252**(2):370-375.

32. Yurkovich M, Avina-Zubieta JA, Thomas J, Gorenchtein M, Lacaille D. **A systematic review identifies valid comorbidity indices derived from administrative health data**. *J Clin Epidemiol* 2015, **68**(1):3-14.

33. Toson B, Harvey LA, Close JC. **The ICD-10 Charlson Comorbidity Index predicted mortality but not resource utilization following hip fracture**. *J Clin Epidemiol* 2015, **68**(1):44-51.

34. Jackson TJ, Michel JL, Roberts RF, Jorm CM, Wakefield JG. **A classification of hospital-acquired diagnoses for use with routine hospital data**. *Med J Aust* 2009, **191**(10):544.

35. Moore L, Lavoie A, Sage NL, Bergeron É, Émond M, Liberman M, Abdous B. **Using Information on Preexisting Conditions to Predict Mortality From Traumatic Injury**. *Ann Emerg Med* 2008, **52**(4):356-364.e352.

36. Australian Consortium for Classification Development. **The international statistical classification of diseases and related health problems, tenth revision, australian modification (ICD-10-AM/ACHI/ACS) (Tenth ed.)**. Darlinghurst, NSW: Independent Hospital Pricing Authority; 2012.

37. **Master linkage key quality assurance report** http://www.cherel.org.au/quality-assurance. Accessed 28 June 2018.

38. SAS Institute. **SAS software, Version 9.4.** Cary, NC, USA: SAS Institute Inc.; 2002-2012.

39. StataCorp. **Stata Statistical Software: Release 14**. College Station, TX: StataCorp LP; 2015.

40. AIHW:Pointer SC. **Trends in hospitalised injury, Australia, 1999–00 to 2010–11**. *Injury research and statistics series no 86 Cat no INJCAT 162.* Canberra: AIHW; 2013.

41. Halfon P, Eggli Y, van Melle G, Chevalier J, Wasserfallen J-B, Burnand B. **Measuring potentially avoidable hospital readmissions**. *J Clin Epidemiol* 2002, **55**(6):573-587.

42. **Potentially avoidable readmissions.** http://www.sqlape.com/AR_ALGORITHM.htm. Accessed 13 March 2018.

43. Donzé J, Lipsitz S, Bates DW, Schnipper JL. **Causes and patterns of readmissions in patients with common comorbidities: retrospective cohort study**. *BMJ : British Medical Journal* 2013, **347**.

44. Donzé J, Aujesky D, Williams D, Schnipper JL. **Potentially avoidable 30-day hospital readmissions in medical patients: Derivation and validation of a prediction model**. *JAMA Internal Medicine* 2013, **173**(8):632-638.

45. Osler T, Rutledge R, Deis J, Bedrick E. **ICISS: An International Classification of Disease-9 Based Injury Severity Score**. *J Trauma Acute Care* 1996, **41**(3):380-388.

46. Australian Institute of Health and Welfare: Henley G & Harrison JE. **Injury severity scaling: A comparison of methods for measurement of injury severity**. *Injury technical paper series no 10.* Canberra: AIHW; 2009.

47. Quan H, Sundararajan V, Halfon P, Fong A, Burnand B, Luthi J-C, Saunders L, Duncan , Beck C, A. , Feasby T, E. , Ghali W, A. . **Coding Algorithms for Defining Comorbidities in ICD-9-CM and ICD-10 Administrative Data**. *Med Care* 2005, **43**(11):1130-1139.

48. Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. **New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality**. *J Clin Epidemiol* 2004, **57**(12):1288-1294.

49. Lin M, Jr HCL, Shmueli G. **Research Commentary—Too Big to Fail: Large Samples and the p-Value Problem**. *Information Systems Research* 2013, **24**(4):906-917.

50. Akaike H. **A new look at the statistical model identification**. *IEEE Trans Automat Contr* 1974, **19**(6):716-723.

51. Dziak JJ, Coffman DL, Lanza ST, Li R. **Sensitivity and specificity of information criteria**. *Technical Report Series, #12.* Pennsylvania USA: The Pennsylvania State University; 2012: 119.

52. Hosmer D, Lemeshow S. **Applied Logistic Regression, 2nd Edition**, vol. 2nd Edition, 2nd edn. New York: John Wiley & Sons, Inc.; 2000.

53. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **Complications, burden and in-hospital death among hospital treated injury patients in Victoria, Australia: a data linkage study**. *BMC Public Health* 2019, **19**(1):798.

54. Fernando DT, Berecki-Gisolf J, Newstead S, Ansari Z. **The Australian Injury Comorbidity Index to predict mortality**. *Ann Emerg Med* 2020, **75**(3):339-353.

55. Morris JA, Jr, MacKenzie EJ, Edelstein SL. **The effect of preexisting conditions on mortality in trauma patients**. *JAMA* 1990, **263**(14):1942-1946.

56. McGwin Jr G, MacLennan PA, Fife JB, Davis GG, Rue III LW. **Preexisting conditions and mortality in older trauma patients**. *J Trauma Acute Care* 2004, **56**(6):1291-1296.

57. Mackenzie JE, Morris AJ, Edelstein LS. **Effect of pre-existing disease on length of hospital stay in trauma patients**. *J Trauma* 1989, **29**(6):757-765.

58. Goldstein LB, Samsa GP, Matchar DB, Horner RD. **Charlson Index Comorbidity Adjustment for Ischemic Stroke Outcome Studies**. *Stroke* 2004, **35**(8):1941-1945.

59. Preen DB, Holman CDAJ, Spilsbury K, Semmens JB, Brameld KJ. **Length of comorbidity lookback period affected regression model performance of administrative health data**. *J Clin Epidemiol* 2006, **59**(9):940-946.

60. Gabbe BJ, Magtengaard K, Hannaford AP, Cameron PA. **Is the Charlson Comorbidity Index Useful for Predicting Trauma Outcomes?** *Acad Emerg Med* 2005, **12**(4):318-321.

61. Neuhaus V, M.D., King, J., B.A., Hageman, M. G., M.D., & Ring, David C,M.D., PhD. **Charlson comorbidity indices and in-hospital deaths in patients with hip fractures**. *Clin Orthop Relat Res* 2013, **471**(5):1712-1719.

62. Lee DS, Donovan L, Austin PC, Gong Y, Liu PP, Rouleau JL, Tu JV. **Comparison of coding of heart failure and comorbidities in administrative and clinical data for use in outcomes research**. *Med Care* 2005, **43**(2):182-188.

63. Stavem K, Hoel H, Skjaker SA, Haagensen R. **Charlson comorbidity index derived from chart review or administrative data: agreement and prediction of mortality in intensive care patients**. *Clin Epidemiol* 2017, **9**:311-320.

64. Nguyen TQ, Simpson PM, Braaf SC, Cameron PA, Judson R, Gabbe BJ. **Comparison of the performance of mental health, drug and alcohol comorbidities based on ICD-10-AM and medical records for predicting 12-month outcomes in trauma patients**. *BMC Health Serv Res* 2018, **18**:408.

65. Price J, Estrada CA, Thompson D. **Case Study**. *Am J Med Qual* 2003, **18**(1):38-45.

66. Daly S, Nguyen TQ, Gabbe BJ, Braaf S, Simpson P, Ekegren CL. **Agreement between medical record and administrative coding of common comorbidities in orthopaedic trauma patients**. *Injury* 2019, **50**(7):1277-1283.

67. Calvo RY, Lindsay SP, Edland SD, Macera CA, Wingard DL, Ohno-Machado L, Sise MJ. **The differential associations of preexisting conditions with trauma-related outcomes in the presence of competing risks**. *Injury* 2016, **47**(3):677-684.

68. MacKenzie EJ, Rivara FP, Jurkovich GJ, Nathens AB, Frey KP, Egleston BL, Salkever DS, Scharfstein DO. **A National Evaluation of the Effect of Trauma-Center Care on Mortality**. *N Engl J Med* 2006, **354**(4):366-378.

69. Neville AL, Brown CVR, Weng J, Demetriades D, Velmahos GC. **Obesity Is an Independent Risk Factor of Mortality in Severely Injured Blunt Trauma Patients**. *Arch Surg* 2004, **139**(9):983-987.

70. Hwabejire JO, Kaafarani HA, Lee J, et al. **Patterns of injury, outcomes, and predictors of in-hospital and 1-year mortality in nonagenarian and centenarian trauma patients**. *JAMA Surgery* 2014, **149**(10):1054-1059.

71. Curtis K, Chan DL, Lam MK, Mitchell R, King K, Leonard L, D'Amours S, Black D. **The injury profile and acute treatment costs of major trauma in older people in New South Wales**. *Australas J Ageing* 2014, **33**(4):264-270.

72. Kuwabara K, Matsuda S, Imanaka Y, Fushimi K, Hashimoto H, Ishikawa KB, Horiguchi H, Hayashida K, Fujimori K, Ikeda S. **Injury severity score, resource use, and outcome for trauma patients within a Japanese administrative database**. *J Trauma Acute Care* 2010, **68**(2):463-470.

73. Moore L, Lauzier F, Stelfox HT, Kortbeek J, Simons R, Berthelot S, Clément J, Bourgeois G, Turgeon AF. **Derivation and Validation of a Quality Indicator to Benchmark In-Hospital Complications Among Injury Admissions**. *JAMA Surgery* 2016, **151**(7):622-630.

74. Moore L, Lauzier F, Stelfox HT, Le Sage N, Bourgeois G, Clément J, Shemilt M, Turgeon AF. **Complications to evaluate adult trauma care: An expert consensus study**. *J Trauma Acute Care* 2014, **77**(2):322-330.

75. Kao LS, Todd SR, Moore FA. **The impact of diabetes on outcome in traumatically injured patients: an analysis of the National Trauma Data Bank**. *The American journal of surgery* 2006, **192**(6):710-714.

76. Tai D, Dick P, To T, Wright JG. **Development of Pediatric Comorbidity Prediction Model**. *Arch Pediatr Adolesc Med* 2006, **160**(3):293-299.

77. Torres-Espíndola LM, Demetrio-Ríos J, Carmona-Aparicio L, Galván-Díaz C, Pérez-García M, Chávez-Pacheco JL, Granados-Montiel J, Torres-Ramírez de Arellano I, Aquino-Gálvez A, Castillejos-López MDJ. **Comorbidity Index as a Predictor of Mortality in Pediatric Patients With Solid Tumors**. *Frontiers in Pediatrics* 2019, **7**(48).

78. Rhee D, Salazar JH, Yiyi Z, Jingyan Y, Yang J, Papandria D, Ortega G, Goldin AB, Rangel SJ, Chrouser K *et al*. **A novel multispecialty surgical risk score for children.** *Pediatrics* 2013, **131**(3):e829–e836.

79. Bergeron LE, Rossignol LM, Osler LT, Clas LD, Phd LA. **Improving the TRISS Methodology by Restructuring Age Categories and Adding Comorbidities**. *J Trauma* 2004, **56**(4):760-767.

80. Michel JL, Cheng D, Jackson TJ. **Comparing the coding of complications in Queensland and Victorian admitted patient data**. *Aust Health Rev* 2011, **35**(3):245-252.

81. van Walraven C, Austin PC, Jennings A, Quan H, Forster AJ. **A modification of the Elixhauser comorbidity measures into a point system for hospital death using administrative data**. *Med Care* 2009:626-633.

82. Toson B, Harvey LA, Close JCT. **New ICD-10 version of the Multipurpose Australian Comorbidity Scoring System outperformed Charlson and Elixhauser comorbidities in an older population**. *J Clin Epidemiol* 2016, **79**:62-69.

83. Faber J, Fonseca LM. **How sample size influences research outcomes**. *Dental Press J Orthod* 2014, **19**(4):27-29.

84. Armijo-Olivo S, Warren S, Fuentes J, Magee DJ. **Clinical relevance vs. statistical significance: Using neck outcomes in patients with temporomandibular disorders as an example**. *Man Ther* 2011, **16**(6):563-572.