Association of Hospital Workload Indicators with Adverse Events: A Retrospective Analysis of Hospital Episode Data

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Abstract

Background: The high prevalence of Adverse Events (AEs) in Australian hospitals and their effects on patient outcomes is a major concern among healthcare service organizations and authorities. The contributing factors which exacerbate this situation, such as the effect of intensified hospital workload on AEs have not been adequately examined in the previous literature. The few studies that have concentrated on the association of hospital workload with AEs have methodological drawbacks due to insufficient numbers of Hospital Workload Indicators (HWIs) employed and the limitation of dimensions that include different types of HWIs.

Aim: This thesis aims to examine the association of HWIs with AEs using indicators drawn from a hospital episode dataset.

Method: This thesis utilized the Classification of Hospital-acquired Diagnosis (CHADx) to capture and categorize AEs from hospital-acquired complications. For this purpose, the patient complications (obtained from the patient secondary diagnoses) need to genuinely represent an AE or be acquired due to a hospital-related external cause code. The relationship between HWIs and AEs was conceptualized by the association of patient exposure to HWIs linked to a patient's AEs acquired during the patient's length of stay (LOS). The patient exposure to HWIs was obtained by three measurements, namely: exposure to peak of daily values of HWIs during the entire patient's LOS, exposure to median of daily values of HWIs during the entire patient's LOS, and exposure to HWIs on the first day of patient's LOS.

Findings: The findings of this thesis suggested the stronger effect of few dimension of HWIs (such as bed occupancy) on increased likelihood of AEs particularly when peak measurement was employed. Moreover, these effects could vary significantly when the effect of HWIs on AEs was analysed within different types of patients. Additionally, the effect of HWIs on AEs could significantly differ when different types of AEs (CHADx categories) were employed.

Conclusion: To the knowledge of the researcher, no previous study has utilized CHADx to identify AEs from hospital-acquired complications. Therefore, this thesis is the first study to examine the association of HWIs with AEs using the CHADx tool.

Student Declaration

I, Mahdi Bazarganigilani, declare that the PhD thesis entitled [Association of Hospital Workload Indicators with Adverse Events: A Retrospective Analysis of Hospital Episode Data] is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature

Date

March 2016

Dedication

I wish to dedicate this thesis to my beloved mother, Mina. You have always encouraged, inspired and instilled in me the values of diligence, patience, punctuality, and meticulousness that have helped me complete this study.

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Technical Terms

Activity Based Funding (ABF):

ABF is management tool for reimbursement of public hospitals by the government, based on the intensity of hospital activities and efficiency of hospital healthcare service delivery (Council of Australian Governments - COAG, 2009).

Adjacent DRG:

Adjacent DRGs are the collapsed version of DRGs, which do not take into account the effect of comorbid conditions or complication diseases into assignment of a DRG.

Adjusted models:

Adjusted models of HWIs with AEs are constructed by statistical relational models in which the effect of each HWI is adjusted by the effect of other HWIs.

Admission date:

A date on which a patient episode of care is started (Health Data Standards Committee - HDSC, 2008).

Adverse Event (AE):

According to the Australian Commission on Safety and Quality in Health Care (ACSQHC) (2012, p. 5), an AE is "an incident in which harm[1] resulted to a person receiving health care". Based on this definition, the underlying cause of the AE occurs following admission to hospital.

Australian Refined Diagnosis Related Group (AR-DRG):

According to the Australian Institute of Health and Welfare (AIHW) (2013, para. 2), AR-DRG is defined as "an Australian admitted patient classification system which

[1] For more explanation on 'harm', readers are referred to its definition in this document, page 3.

provides a clinically meaningful way of relating the number and type of patients treated in a hospital (casemix) to the resources they required".

Casemix:

An information tool used to classify the patient episode of care into clinically meaningful and similar categories based on hospital resources or activities they need or the cost they incur to the hospital (Eagar & Hindle, 1994).

Charlson comorbidity index:

The Charlson comorbidity index (Charlson, Pompei, Ales, & MacKenzie, 1987) is one of the commonly used comorbidity indexes in the literature. This index assigns a severity score to each comorbid condition based on prediction of ten-year mortality rate in patients having the same comorbid condition (Charlson et al., 1987).

Classification of Hospital-acquired Diagnosis (CHADx):

According to Utz, Johnston, and Halech (2012, p. 1): "CHADx offers a comprehensive classification of hospital-acquired conditions available for use with ICD-10-AM".

Comorbid conditions:

Comorbid conditions refer to diseases that co-exist with each other at the time of admission. However, the main underlying disease known as primary diagnosis and is not considered as a comorbid condition (Jakovljević & Ostojić, 2013).

Diagnosis Related Group (DRG):

According to Fetter, Shin, Freeman, Averill, and Thompson (1980, p. 3), "the fundamental purpose of the DRG approach is to identify in the hospital acute-care setting a set of case types, each representing a class of patients with similar processes of care and a predictable package of services".

Episode of care:

A period of health care related to an individual patient that has a start and ending date (HDSC, 2008).

Harm:

According to the World Health Organization (WHO) (2009, p. 16), harm "implies impairment of structure or function of the body and/or any deleterious effect arising therefrom, including disease, injury, suffering, disability and death, and may be physical, social or psychological".

Hospital episode dataset:

Hospital episode datasets contain the discharge information of all patients who are admitted within hospitals. Different hospital episode datasets (for example as implemented in different hospitals or different states) consist of different fields and structure (Department of Health - State of Queensland, 2012; Department of Health - State of Victoria, 2012; Department of Health - State of Western Australia, 2014).

Hospital Workload Indicators (HWIs):

HWIs are employed to conceptualize, measure and estimate the intensity of workload within hospitals.

International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification (ICD-10-AM):

ICD-10-AM includes extensions of the WHO's ICD-10 codes and some specific diseases codes that are used within Australian hospital context (Roberts, Innes, & Walker, 1998).

Length of Stay (LOS):

The LOS of a patient is measured in patient days representing the duration of patient's hospitalisation. Same day patients have LOS of one (HDSC, 2008).

Major Diagnostic Category (MDC):

MDCs categorize diseases and their corresponding ICD (International Classification of Diseases) codes within similar traits or characteristics. The diseases in each MDC are associated with a particular organ in the human body.

National Hospital Cost Data Collection (NHCDC):

NHCDC is an annual and voluntary repository of Australian hospitals' activities and cost data collection. This dataset is used annually to produce and update AR-DRG cost weights related to national public and private sectors.

Nursing DRG cost weight:

Nursing DRG cost weight is a component of a DRG cost weight and only includes costs associated with nursing care in general ward areas (Independent Hospital Pricing Authority (IHPA), 2004).

Patient adverse outcomes:

Patient adverse outcomes are measurements of deficiency and deterioration of quality of healthcare service delivery within hospital environments (IHPA, 2011). For example, AEs, in-hospital mortality, readmission rate, prolonged LOS and extensive costs are examples of patient adverse outcomes.

Patient-level analysis:

In this thesis, this term refers to an adjusted model of HWIs with AEs when the association between patient exposure to HWIs and the likelihood of a patient‘s AE is examined. Therefore, the unit of analysis of AEs in a patient-level analysis is the patient.

Primary diagnosis:

The primary diagnosis is the diagnosis mainly responsible for occasioning a patient episode of care or patient attendance at healthcare service provider (HDSC, 2008).

Secondary diagnosis:

A secondary diagnosis is a condition or disease that coexists with the primary diagnosis (comorbid condition) or is acquired during hospitalisation (such as AEs) within a patient episode of care (HDSC, 2008).

Victorian Admitted Episode Dataset (VAED):

VAED consists of "demographic, clinical and administrative details for every admitted episode of care occurring in Victorian hospitals, rehabilitation centres, extended care facilities and day procedure centres" (Department of Health - State of Victoria, 2014b, p. 4).

Weighted Inlier Equivalent Separation (WIES):

WIES is "a cost-weighted separation and is calculated using different cost weights (weighted) for different types of patient stay (inlier equivalent separation) within each DRG" (Department of Health - State of Victoria, 2014d, p. 45). It is expected that episodes of care having identical DRGs but having higher LOSs incur higher costs to the hospital. Therefore, WIES adjusts the DRG cost weight by the episode's LOS when used for hospital reimbursement planning. In 2014-2015 major metropolitan public hospitals in Victoria received $4,385 per WIES for the reimbursement of patients' treatment (Department of Health - State of Victoria, 2014d).

Chapter 1: Introduction

1.1 Background and Problem Statement

Adverse Events (AEs) are one measurement of patient adverse outcomes and can be used to measure hospital performance and quality of healthcare service delivery (Jackson, Moje, Shepheard, & McMillan, 2009). According to the ACSQHC (2012, p. 5), an AE is "an incident in which harm resulted to a person receiving health care". Harm "implies impairment of structure or function of the body and/or any deleterious effect arising therefrom, including disease, injury, suffering, disability and death" (WHO, 2009, p. 16). Some examples of AEs include complications due to hospital treatment, falls resulting in injuries, and medication errors resulting in a patient harm (AIHW, 2014a).

The prevalence of AEs in hospitals and their contribution to adverse outcomes has become a problem on a number of levels. Hospitals incur extensive costs due to AEs (Jackson, Nghiem, Rowell, Jorm, & Wakefield, 2011). This extensive cost is the result of serious complications and injuries that are outcomes of an AE that lead to additional treatments and prolonged length of stay (LOS) (Jackson et al., 2011). Moreover, AEs result in patient dissatisfaction with underlying hospital treatment (Ohnmeiss, Bodemer, & Zigler, 2010) and furthermore, AEs increase the likelihood of other serious adverse outcomes such as in-hospital mortality (Kim et al., 2013; Kim et al., 2012). Recent statistics indicate:

- 5.5% of hospital admissions within Australian hospitals (6.5% for public hospitals and 4.0% for private hospitals) in 2012-13, resulted in an AE (AIHW, 2014b);
- AEs contribute to 17.3% of additional treatment costs within the states of Victoria (2005-06) and Queensland (2006-07) (Jackson et al., 2011);
- AEs add AU$790 million to costs of inpatient care in the states of Victoria (2005-06) and Queensland (2006-07) (Jackson et al., 2011);
- On average, patients with an AE stay 10 days longer in Victorian hospitals (Department of Health - State of Victoria, 2014a);

- The average cost of each AE in Victoria is $6,826 (Department of Health - State of Victoria, 2014a).

The prevalence of AEs in hospitals as demonstrated by the above figures highlights the importance of research to examine the contributing factors that have a bearing on the increased likelihood of patients' AEs. A recent line of research inquiry has suggested that hospital workload, measured by the rate of admissions, discharges and bed occupancy, may increase the likelihood of patients' AEs (Duffield et al., 2011; Weissman et al., 2007). This study extends this line of inquiry to investigate the question: Is there a relationship between variation in hospital workload and the likelihood of patients' AEs? Also, what aspect or dimensions of hospital workload may intensify the likelihood of patients' AEs?

The factors that contribute to an increased likelihood of patients' AEs are complex and multi-faceted. For example, the complex nature of hospital systems[2] contributes to the cause of occurrences of errors (Perrow, 2011). Hospitals consist of many inter-correlated components such as hospital units and departments. This structure helps the hospital to sustain an amount of redundancy in workload through a buffering mechanism (Perrow, 2011). For example, when the hospital is overcrowded, patients may wait longer in the emergency departments (EDs). Furthermore they may be cared for in wards or in recovery rooms when ICU beds are unavailable (Weissman et al., 2007). Thus, in the above examples, EDs, wards and recovery rooms serve a buffering capacity for the whole hospital system. Still, hospital over-crowding puts additional pressures on these departments which consequently makes them prone to higher rates of errors and AEs.

[2] According to the General System Theory proposed by Von Bertalanffy (1968, p. 43), "A system is an entity which maintains its existence through the mutual interaction of its parts". These parts usually contain interacting elements. These elements have a hierarchical nature in which each level of the hierarchy comprises a subsystem of interrelated elements. The interactions between subsystems or their elements are dynamic and as a whole comprise a complex and inter-correlated object (Von Bertalanffy, 1968).

Nevertheless, with an influx of patients to the system (hospital and hospital departments) the buffering capacity can become overloaded. The influx into the system can be equivalently explained by the patient turnover or the 'churn' phenomenon (transfer of patients between different departments). Patient turnover or churn creates an unstable work environment (Duffield et al., 2011). It is accompanied with increases in patients' transfers with possible communication gaps between the staff of transferred and transferring departments (Duffield et al., 2011). As a result of these communication gaps, patients become even more likely to face errors and AEs (Duffield et al., 2011). Overall, higher patient turnover is expected to increase the hospital rates of errors and AEs (Duffield et al., 2011; Weissman et al., 2007).

In summary, literature has confirmed that when hospitals faced higher workload, the rates of patient adverse outcomes such as medication errors (Duffield et al., 2011; Tibby, Correa-West, Durward, Ferguson, & Murdoch, 2004), AEs (Duffield et al., 2011; Pedroja, 2008; Weissman et al., 2007) and in-hospital mortality (Kuntz, Mennicken, & Scholtes, 2011, 2014) increased significantly.

1.2 Activity Based Funding (ABF)

This study is conducted using the technologies provided by ABF. ABF is a management tool for reimbursement of public hospitals by the government, based on the intensity of activities and healthcare services they provide (COAG, 2009). In other words, ABF is a scheme where the government funds hospitals based on the case-mix of the patients. On November 29, 2008, the Council of Australian Governments (COAG) agreed to a national partnership plan to improve hospital efficiency by implementing ABF in all Australian jurisdictions. Since the implementation of a national approach to ABF in Australia, it is a mandatory task for hospitals to report all operational activities and to maintain this information as a part of good hospital management practice (COAG, 2009; Department of Health - State of Victoria, 2014c). Hospital episode datasets have been created to record all information related to the hospitalisation and treatment of each patient.

1.3 Hospital Episode Dataset

This study uses a hospital episode dataset to examine the association between workload in hospitals and AEs. According to Heslop (2014, p. 472), the term 'hospital episode data' has other surrogate terms in the literature such as 'hospital administrative data', 'routine inpatient data', 'hospital morbidity data', 'casemix data' and 'discharge data'. Hospital episode datasets contain all the information of patients who are admitted to hospital. When a patient is admitted to a hospital, certain procedures involving treatment occur. The patient is allocated a primary diagnosis that denotes the underlying cause of hospitalisation. In addition to the primary diagnosis, other secondary diagnoses may be present at the time of admission such as comorbid conditions. Other conditions may be acquired during hospitalisation such as hospital-acquired complications and AEs that are recorded in the patient's secondary diagnoses. Additionally, the patient is allocated a primary procedure which is the main procedure to be undergone for treatment. The patient may also undergo several secondary procedures. In summary, all the information regarding the patient's demographic characteristics, for example, primary diagnosis and primary procedure, secondary diagnoses and secondary procedures, and discharge status are commonly recorded into a hospital episode dataset (Department of Health - State of Queensland, 2012; Department of Health - State of Victoria, 2012; Department of Health - State of Western Australia, 2014). This information in the dataset can be extracted and used for conducting healthcare service research.

Various coding schemes are employed within different countries to computerize and code patients' medical records following discharge. In Australian hospitals, patients' diagnoses are coded based on the International Statistical Classification of Diseases and Related Health Problems, Australian Modification (ICD-10-AM). Procedures are coded based on the Australian Classification of Health Interventions (ACHI). Finally, each patient's episode of care is assigned to a Diagnosis Related Group (DRG)[3]. These codes are used to reimburse hospitals based on the intensity of care associated

[3] DRGs are a patient classification system that provides a meaningful way of relating the types of patients treated in a hospital to clinically similar groups based on the resources they require (Fetter et al., 1980).

with the patient's episode of care (DRG group) and episode's LOS (IHPA, 2011). In other words, the required resources associated with a DRG group reflect the amount of hospital activity undertaken for treatment of similar patients within that DRG. Each year, all hospitals, in various states and territories across Australia, submit the information regarding patients' episodes of care to their jurisdiction's Department of Health to form the jurisdiction's episode dataset. For Victoria, this dataset is named the Victorian Admitted Episode Dataset (VAED) (Department of Health - State of Victoria, 2012). This is the dataset used in this study.

1.4 Classification of Hospital-Acquired Diagnoses (CHADx)

ABF mandates the storing of patient information into hospital episode datasets. Accordingly, this thesis employs CHADx for identification of AEs from a hospital episode dataset. CHADx was developed by researchers at the Australian Centre for Economic Research on Health (ACSQHC) to overcome the lack of standards for recording hospital-acquired complications (ACSQHC, 2010). CHADx is a classification tool available to hospitals to monitor hospital-acquired complications based on ICD-10-AM codes.

CHADx includes a wide range of hospital-acquired complications that can be employed to potentially capture a wide range of AEs based on external cause codes of hospital-acquired complications. It should be noted, this thesis is not confined to the hospital-acquired complications which are provided by CHADx[4] to identify AEs. Any diagnosis as a result of a hospital-related external cause code obtained during hospitalisation (complication) is considered as an AE. CHADx provides a standard and consistent tool for identification of hospital-acquired complications based on many different categories of diagnoses. Therefore, it is an effective tool for the categorization of prospective AEs to assist with this thesis' analyses.

[4] The diagnoses which are not captured by CHADx categories and are due to a hospital related external cause code (AE) are categorized in CHADx 17 (other complications). For more details readers are referred to Chapter 3, Section 3.4: Identification of AEs from CHADx.

It should be also noted that while CHADx provides hospitals with a tool for the identification of a wide range of hospital-acquired complications, it is not intended to be employed as an external monitoring tool of hospital performance. In other words, it does not aim to hold hospitals accountable for low quality of patient safety indicators such as occurrences of hospital-acquired complications and AEs (Utz et al., 2012).

1.5 Hospital Workload Indicators (HWIs)

In this thesis, hospital workload is conceptualized by HWIs, which are extractable from hospital episode datasets. The extraction of HWIs from an episode dataset is associated with numerous advantages. Firstly, any research based on a secondary source of data, such as a hospital episode dataset, is more cost and time effective in comparison to other methods which need direct commitment from nurses and patients (Dunn, Arslanian-Engoren, DeKoekkoek, Jadack, & Scott, 2015). Secondly, research based on the secondary source of data is involved with less risk for participants (patients) and is associated with higher confidentially for the participants (Dunn et al., 2015). This is because the sensitive information regarding participants is usually not recorded into hospital episode data, or when it is, the information is recorded in an unidentifiable format. Moreover, due to the cost and time effectiveness of conducting research based on hospital episode data, the research could be extended to larger scale investigations (Dunn et al., 2015).

HWIs should be conceptualized by robust dimensions if they are to truly represent the hospital workload. This thesis employs the model of Weissman et al. (2007) which identifies comprehensive dimensions of HWIs based within four main categories:

- Volume (e.g. bed occupancy);
- Throughput (e.g. number of admissions, number of discharges);
- Patient complexity (e.g. DRG cost weight); and
- Nurse staffing and workload (e.g. nurse to patient ratio)[5].

[5] It should be noted that while Weissman et al. (2007) proposed a comprehensive suite of HWIs in their conceptual model, in the implementation phase, they used these indicators separately. This posed a significant drawback while representing the association of each HWI with AEs. This drawback is explained in detail in the following chapter (Chapter2, Section 2.3.1.4: Hospital).

1.6 Aim and Objectives

The overall aim of the thesis is to examine the association of HWIs with AEs by using data elements (variables) drawn from a hospital episode dataset. The objectives are further divided into five main phases:

1. To review the literature for evidence of the association between HWIs and AEs and to discuss the major drawbacks and limitations of current approaches;
2. To develop a reliable and accurate adjusted (relational) model to explore the association of HWIs with AEs;
3. To develop a composite index of HWIs which predicts the likelihood of a patient's AE;
4. To analyse the effect of HWIs on particular types of AEs according to CHADx categories;
5. To examine the effect of different types of AEs (CHADx categories) on each other after adjusting for the effect of HWIs (this is the result of the fourth objective).

1.7 Significance of the Study

First of all, this study is significant because of the extensive rates of AEs within Australian hospitals (AIHW, 2014b; Jackson et al., 2011) and understandings of the contributing factors to AEs is important. Secondly, health service officials and clinicians have increasingly raised workloads as a possible factor linked to AEs. HWI's are important to investigate for their effects on AE's as these indicators are measures of workload. Thirdly, the effects of workload on AE's have been overlooked. This situation is of concern to health policy officials on many levels. This study is one of the first pilot studies in Australia to investigate the association of HWIs with AEs. Fourthly, this study contributes to the improvement of patient safety by investigating the association between HWIs and AEs. AEs have been proven to have significant adverse effects on hospital performance and patient outcomes; thus any well-designed study that examines the contributing factors and their causes, such as HWIs, is of great importance. Fifthly, there is limited international research which investigates the association of HWIs with AEs and any research conducted to date

required improvement to current methodologies. Finally, the findings of this thesis are expected to provide insights for hospital authorities and policy makers to understand the impact of workload on AEs. Therefore, the findings of this thesis may contribute to decision-making by policy makers, such as better handling of resources or by prioritizing efforts toward managing workloads.

1.8 Adjusted Models of HWIs with AEs

The association of HWIs with AEs is obtained by construction of an adjusted model. An adjusted model is a statistical relational model that employs HWIs as independent indicators linked to AEs as a dependent indicator. The model is described as 'adjusted' since the effect of a HWI on AEs is adjusted by the effect of other HWIs, which could have a substantial effect on AEs as well. In this thesis, the adjusted model is constructed by a comprehensive suite of HWIs using the four dimensions, as proposed by Weissman et al. (2007). Using these comprehensive dimensions of HWIs avoids an overestimated association between the HWI and AEs. As a consequence, a more reliable adjusted model is obtained to represent the association between a HWI and AEs.

1.9 Research Questions

The main questions that have arisen, which address the research aim of this study are as follows:

1. How has the association of HWIs with AEs been analysed and examined in the literature?
2. Which HWIs have the greatest effect on the increased likelihood of patients' AEs?
3. Do HWIs have different effects on different types of AE as identified by CHADx categories?
4. What is the difference between the associations of HWIs with AEs, among different types of patients, such as medical versus surgical patients?
5. Is there any relationship among occurrences of different types of AEs, and how much do they affect the likelihood of each other?

1.10 Thesis Organisation

This thesis addresses the research aims and questions systematically through five chapters. This chapter has introduced the research domain, thesis' aims, objectives and its structure. Chapter 2 reviews the literature on the association of HWIs with a variety of patient adverse outcomes including AEs and hospital-acquired complications. Major gaps and limitations exposed in the literature are explained. Chapter 3 comprises the design and methodology, proposes the thesis' conceptual framework, the approach for utilization of CHADx to identify AEs from hospital-acquired complications, and methods and procedures for establishing the adjusted models of HWIs with AEs. Chapter 4, examines findings and discussions, implements the thesis' conceptual framework and presents the obtained results and discusses their implications. Chapter 5 presents the conclusion of the thesis, major strengths and limitations and also some suggestions for future research.

Chapter 2: Literature Review

2.1 Questions to Structure the Literature Review

To structure this literature review, this chapter intends to answer three main questions. As this thesis aims to examine the association of HWIs with AEs, this review firstly answers the question of how HWIs affect the increased likelihood of patients' AEs. Secondly, this review seeks to discover how AEs are utilized in the literature. Thirdly, this review investigates whether studies that examined the association of HWIs with AEs have employed a reliable and accurate adjusted model to represent the association. To answer this question, possible methodological flaws and drawbacks in the adjusted models employed in the literature are addressed and suggestions for their correction are provided.

Although this study seeks to examine the association between HWIs and AEs, for the purpose of this review, more untoward events such as medication errors and hospital-acquired complications were included. The justification behind these inclusions is provided in this chapter. Following an in-depth review of the relevant studies, trends of the association between each dimension of HWIs and AEs are obtained and discussed.

2.2 Inclusion and Exclusion Criteria

As a part of the literature review, this chapter has included studies published after 2000. Various scientific online databases such as Scopus, Pubmed, Medline, CINAHL, ProQuest and Google Scholar search engine were used to identify academic studies. Journal rankings were also applied as a measurement of the quality of publications. Publications were considered for inclusion if they appeared in the first three highest journal rankings (Q1, Q2, Q3) of the SCImago ranking system, meaning that such papers are not in the lowest ranked journals in a given discipline. To search the databases, terms such as hospital workload, Hospital Workload Indicators (HWIs), adjusted models, adverse events (AEs), adverse effects of HWIs, complications, medication errors and adverse outcomes were chosen.

The search using the above terms generated a high numbers of studies. After careful consideration of the title and abstract of the publications, 49 studies were found that examined the association of HWIs with a variety of patient adverse outcome indicators. However, very few of these studies examined the association of HWIs with AEs. Therefore, a strategy including a set of inclusion and exclusion criteria based on both HWIs and adverse outcomes

employed in the studies, was formulated. The inclusion criteria extended the range of the studies to those which employed wider ranges of adverse outcomes that are closely associated with AEs. This was necessary to strengthen the conclusion of this review, examining the association of each dimension of HWIs with AEs. The exclusion criteria confined the studies to those more relevant to the scope of this thesis.

2.2.1 Adverse outcomes

From the initial search on association of HWIs with patient adverse outcomes (n = 49), based on the employed measurement of patient adverse outcomes, some studies were included in this review while others were not. This section provides the details of the inclusion and exclusion criteria for the measurement of patient adverse outcomes that were employed in this review.

This thesis aims to examine the association of HWIs with AE, thus AEs are the prime adverse outcomes indicator in this review. AEs have a wide range of definitions in the literature (Department of Health - The UK Government, 2000). Some of these definitions are very broad. For example, Webb et al. (1993, p. 520) define AEs as an incident or disease that "lead to an undesired outcome ranging from increased length of hospital stay to death or permanent disability". Therefore, based on this definition, any medication error or hospital-acquired complication can be considered an AE, since it results in an undesired outcome. Tibby et al. (2004, p. 1160) used a broader definition and identified AEs as "any event which actually or potentially compromises patient care". However, in this thesis, an AE was identified by a narrower definition as "an incident in which harm resulted to a person receiving health care" (ACSQHC, 2012, p. 5) (refer to Chapter 1, Section 1.1: Background and Problem Statement). According to the proposed definition, the harm should be due to the hospital treatment and not due to underlying patient diseases or the severity of illness.

It is notable that in addition to AEs, this review included studies that examined the association of HWIs with medication errors. There were two reasons for this inclusion. Firstly, it is obvious that if medication errors result in patient harm, they represent an AE (ACSQHC, 2012); however, based on a broader definition of AEs suggested by Tibby et al. (2004), medication errors are examples of AEs since they potentially compromise the patient care. Secondly, as medication errors are one of the major sources of AEs (Wilson, Harrison,

Gibberd, & Hamilton, 1999), it follows that any study that examined the association of HWIs with medication errors could suggest a similar trend for AEs as well.

Furthermore, this review sought to include studies which examined the association of HWIs with hospital-acquired complications. Hospital-acquired complications are considered an AE if they are due to a hospital incident or deficiency in the hospital treatment (ACSQHC, 2012). However, it was not possible to determine the cause of complications in some of the studies in this review. Nevertheless, there are two compelling justifications for considering the association of HWIs with hospital-acquired complications in this review. Firstly, based on the broader definition of AEs suggested by Tibby et al. (2004, p. 1160), hospital-acquired complications are considered an AE since they potentially compromise patient care. Secondly, there is close association between occurrences of AEs and hospital-acquired complications. Jackson, Duckett, Shepheard and Baxter (2006) found that 41% of AEs in Victoria Admitted Episode Dataset (VAED) between 2000 and 2001 were a hospital-acquired complication. As previously described, this thesis utilizes CHADx for the identification of AEs from hospital-acquired complication[6], which further supports the close association between occurrences of AEs and hospital-acquired complications based on the context of this thesis.

In summary, it is assumed that there is a very close association between occurrences of medication errors and hospital-acquired complications with AEs. Therefore, the effect of HWIs on medication errors and hospital-acquired complications could be indicative for the effect of HWIs on AEs as well. It should be noted that ADRs are mainly regarded as medication errors, and due to patient harm they represent an AE, However, the definition of medication error can encompass a wide range of human errors which may then result in patient harm (AEs) or not (not an AE).

Additionally, Failure to Rescue (FTR) is identified as death following a complication (Aiken, Clarke, Sloane, Sochalski, & Silber, 2002). Even thought, they are partially assigned to hospital mistreatment of the patient,and thus denote to an AE (ACSQHC, 2012))[7]. Hence, in this review, any study that examined the association of HWIs with FTRs was included.

[6] The detailed explanation regarding the identification of AEs from CHADx has been provided in Chapter 3, Section 3.4: Identification of AEs from CHADx.

[7] It is notable that in this review, in-hospital mortality was not considered as an AE except when it is followed by a hospital-acquired complication (definition of a FTR).

In contrast to the way in which AEs are operationalized in this thesis, for the purpose of this review, studies were not confined to those that extracted adverse outcome indicators from hospital episode datasets. This review included a wider range of studies that used other methods for the extraction of adverse outcomes, namely using hospital incident management reporting systems or chart reviews of patients' medical records. In addition, studies were included if they were conducted in various hospital settings (context). This included the hospital itself, hospital clinical departments or any of the hospital units such as Intensive Care Units (ICUs), Emergency Departments (EDs), and hospital wards.

It is notable that from the initial search on the association of HWIs with patient adverse outcomes (n=49), some studies (n=19) did not meet the above inclusion criteria because they employed measurements of patient adverse outcomes other than AEs, medication errors, or hospital-acquired complications. This included length of stay (LOS) (Berry Jaeker & Tucker, 2012a, 2012b; Giakoumidakis et al., 2012; Kc & Terwiesch, 2012; Pines et al., 2009), mortality (Schilling, Campbell Jr, Englesbe, & Davis, 2010; Tarnow-Mordi, Hau, Warden, & Shearer, 2000; West et al., 2014), readmission rate (Elliott, Worrall-Carter, & Page, 2013; Encinosa & Hellinger, 2008; Evans & Kim, 2006; Mueller, Donzé, & Schnipper, 2013), and cost (Elliott, Young, Brice, Aguiar, & Kolm, 2014; Ong, Bostrom, Vidyarthi, McCulloch, & Auerbach, 2007). It should be noted that it is evident that all aforementioned measurements of patient adverse outcomes such as prolonged LOS, in-hospital morality and readmission could be due to occurrences of AEs as well (Jackson et al., 2011); however, based on the context of this thesis (utilization of AEs from CHADx), it is assumed medication errors and hospital acquired complications could more accurately represent the association of HWIs with AEs.

Moreover, a few studies (Al-Kandari & Thomas, 2009; Elliott et al., 2013; Nielsen, Pedersen, Rasmussen, Pape, & Mikkelsen, 2013) obtained measurement of AEs solely by relying on the perception of the staff; this was usually conducted by using tools such as questionnaires or interviews one day after the time of patient discharge (cross-sectional design). However, this approach has been criticised for the lack of accuracy in the estimation of AEs since the perception of staff can be erroneous or biased (Michel, Quenon, de Sarasqueta, & Scemama, 2004). There were seven studies that followed this criterion which were also excluded from the final review, leaving 23 studies that met the inclusion and exclusion criteria for measurements of patient adverse outcomes. It is notable that for HWIs, further inclusion and exclusion criteria were considered for this review; these are described in the following section.

2.2.2 HWIs

In addition to measurements of patient adverse outcomes, HWIs were further examined to meet the scope of this review. Since this thesis aimed to establish the association of HWIs with AEs using indicators drawn from hospital episode datasets, studies that obtained HWIs from sources other than hospital episode datasets were excluded from this review. This section will provide a brief discussion on the employed HWIs in the literature when linked to patient adverse outcomes. Following this, the rationale behind the inclusion and exclusion based on employed HWIs in this review is provided.

According to Weissman et al. (2007), HWIs can be categorized in four broad dimensions using a variety of indicators. Volume was a prime dimension of HWIs suggested by Weissman et al. (2007), which affects the likelihood of patients' AEs. Weissman et al. (2007) employed bed occupancy to measure hospital volume. It is notable that higher hospital bed occupancy is expected to increase the likelihood of patients' adverse outcomes such as AEs (Epstein et al., 2012; Weissman et al., 2007) and medication errors (Duffield et al., 2011)[8]. Apart from bed occupancy, the ED Work Index (EDWIN) (Bernstein, Verghese, Leung, Lunney, & Perez, 2003) has been developed as a measure of an ED volume. This measure was established to measure the overcrowding of an ED. Epstein et al. (2012) found significant[9] association of higher EDs' EDWIN scores (as a measure of volume indicators) with the increased likelihood of patients' AEs (Epstein et al., 2012). Similarly, Kulstad, Sikka, Sweis, Kelley and Rzechula (2010) found significant association of higher ED's EDWIN score with increased likelihood of patients' medication errors (similar to AEs). Additionally, McCarthy et al. (2008) suggested that this index has a high correlation with bed occupancy, suggesting it may not have any superiority over a much simpler indicator such as bed occupancy (McCarthy et al., 2008). Also, in contrast to bed occupancy, the EDWIN score is not extractable from hospital episode datasets. For these reasons, it was not included in this review.

Throughput is another dimension of HWIs suggested by Weissman et al. (2007). Throughput or turnover refers to the rate at which patients enter and exit from the hospital (Weissman et al., 2007). Two hospitals may have identical volume but experience very different throughput

[8] The detailed information regarding these studies and their associations has been provided in the following section (Section 2.3.1: Volume).

[9] Throughout this thesis, a significant association is denoted when the statistical significance of the null hypothesis (p-value) is less than 0.05.

rates. Therefore, in addition to volume, higher throughput rates also affect the likelihood of patients' AEs (Duffield et al., 2011; Weissman et al., 2007). Weissman et al. (2007) employed the numbers of admissions and numbers of discharges for measuring hospital throughput. Likewise, with bed occupancy/volume, it is expected that higher throughput is associated with the increased likelihood of patients' adverse outcomes (Weissman et al., 2007)[10]. Since, the number of admissions and discharges are extractable from hospital episode datasets, they were included in this review.

Nurse staffing and workload is another dimension of HWIs. Weissman et al. (2007) used patient to nurse ratio to examine the association between nurse staffing levels, as a workload dimension of HWIs, and AEs. The association of hospitals' nurse staffing indicators with the likelihood of patients' AEs has been examined comprehensively in the literature (Kovner, Jones, Zhan, Gergen, & Basu, 2002; Needleman, Buerhaus, Mattke, Stewart, & Zelevinsky, 2002; Schreuders, Bremner, Geelhoed, & Finn, 2015; Unruh, 2003). This association has been examined by different nurse staffing indicators. A large number of studies reported a significant association of higher hospital nurse to patient ratios with the decreased likelihood of a patient's AE (Weissman et al., 2007) and FTR (Aiken et al., 2011; Aiken et al., 2002)[11]. Furthermore, higher hours of care per patient day provided by Registered Nurses (RNs) were associated with a decreased likelihood of patients' AEs (Kovner et al., 2002; Unruh, 2003) and FTR (Needleman et al., 2002). This result has also been supported by three systematic reviews (Blegen, 2006; Kane, Shamliyan, Mueller, Duval, & Wilt, 2007; Pearson et al., 2006). Similarly, a higher hospital skill mix, identified by the proportion of RNs to all other nurses, has been associated with decreased likelihood of patients' AEs (Unruh, 2003). Nevertheless, the aforementioned nurse staffing indicators (nurse to patient ratio, skill mix and hours of care provided by RNs) are not extractable from hospital episode datasets, and are not employed in this thesis for examining their associations with AEs. Therefore, these indicators are beyond the scope of this review.

Other measurements of nurse staffing and workload such as Project Research in Nursing-80 (PRN-80) (Chagnon, Audette, Lebrun, & Tilquin, 1978) have been employed by Duffield et al. (2011) to examine its association with AEs. PRN-80 estimates the hours of care required

[10] The detailed explanation regarding these associations has been provided in the following section (Section 2.3.2: Throughput).
[11] Referring to Section 2.2.1: Adverse outcomes, FTR was considered as an AE.

for the treatment of patient by using completed nursing tasks (Chagnon et al., 1978). However, Duffield et al. (2011) found no association between higher units' PRN-80 scores and increased likelihood of any types of units' AEs. Similar to previously mentioned nurse staffing indicators, such as nurse to patient ratio, skillmix and hours care provided by RNs, PRN-80 is not derivable from a hospital episode dataset; therefore, it is beyond the scope of this review.

Patient complexity is another dimension of HWIs and refers to a patient's case complexity or the severity of the illness[12] (Weissman et al., 2007). It is expected that patients with complex care requirements increase the demands on hospital workload. Therefore, exposure to higher levels of complex patients can result in an increased likelihood of a patient's AE (Weissman et al., 2007). Weissman et al. (2007) used the sum of patients' Diagnosis Related Groups (DRG)[13] cost weights[14] to measure the patient complexity dimension of HWIs. Patient's DRG cost weight is extractable from hospital episode datasets (Department of Health - State of Queensland, 2012; Department of Health - State of Victoria, 2012; Department of Health - State of Western Australia, 2014) and was included in this review.

It should be taken into account, that, in another study, a higher 'individual patient complexity' score (represented by Weighted Inlier Equivalent Separation – WIES[15]) has been associated with an increased likelihood of a patient's AE (Hauck, Zhao, & Jackson, 2012). However, the concept of individual patient complexity is different from the concept of patient exposure to hospital patient complexity employed by Weissman et al. (2007). The latter concept is regarded as one of the dimensions of HWIs whereas the patient individual complexity represents the severity of the illness of the individual patient for hospital treatment.

Within an ICU context, other measures of patient complexity such as Acute Physiology and Chronic Health Evaluation II (APACHE II) and Simplified Acute Physiology Score II (SAPS

[12] The terms 'patient complexity', 'patient intensity', or 'patient severity of illness' are used equivalently throughout this thesis.
[13] A DRG group is assigned to a patient based on his demographic characteristics at the time of discharge such as patient's age, sex, LOS, same day status, mental health legal status, discharge status and the existence of complications or comorbid conditions (Department of Health - State of Western Australia, 2012).
[14] DRG cost weights is relative cost weight for each DRG. Higher DRG cost weights indicate that patients need higher resources and expenditure for hospital treatment. Therefore, DRG cost weight is an effective indicator to measure the patient's case complexity or severity of illness.
[15] According to the Department of Health - State of Victoria (2014d, p. 45), WIES is a cost-weighted separation for each DRG and assigned different weights for each separation based on the separation's LOS.

II) (Le Gall, Lemeshow, & Saulnier, 1993), have been employed in the literature to examine associations of patient individual complexity with AEs (Chaboyer, Thalib, Foster, Ball, & Richards, 2008; De Jong et al., 2013). APACHE II uses 12 routine physiological indicators during the first 24 hours for prediction of patient mortality (Le Gall et al., 1993). SAPS II is a more optimized version of APACHE II which uses slightly different physiological indicators (Le Gall et al., 1993). Similar to Hauck et al. (2012) who showed an association of higher individual patient complexity (WIES score) with an increased likelihood of a patient's AE, De Jong et al. (2013) and Chaboyer et al. (2008) found that a patient with a higher individual patient complexity (represented by SAPS II and APACHE II scores) has a higher likelihood of an AE.

It is notable that in contrast to DRG cost weights, which have been obtained and validated using large cohorts of patients, SAPS II and APACHE II have been obtained from a comparatively small cohort of patients. The APACHE II scores were obtained using a sample of 5,815 ICU patients in 13 US hospitals (Knaus, Draper, Wagner, & Zimmerman, 1985), while SAPS II severity scores were obtained from a sample of 13,152 patients in 137 ICUs in 12 countries (Le Gall et al., 1993). In contrast, the National Hospital Cost Data Collection (NHCDC) between 2011 and 2012 which was used to calculate DRG cost weights in the following year (2013-2014), included 4.717 million admitted acute surgical admissions within 429 Australian hospitals (IHPA, 2014). Therefore, it is not clear whether SAPS II and APACHE II patient complexity indicators represent the severity of the patient's illness as accurately as DRG cost weights. Nevertheless, whether SAPS II and APACHE II scores are employed as hospital workload or as a patient individual complexity indicator, they are not extractable from hospital episode datasets[16] and therefore, they are beyond the scope of this review[17].

[16] It is notable the physiological indicators for calculation of APS II and APACHE II are not extractable from hospital episode datasets.

[17] In this thesis, instead of WIES or DRGs, Adjacent DRGs (A DRG without comorbid conditions) are employed to incorporate patient individual complexity in the analysis. Readers are suggested to refer to the section 3.3.1.2 - Patient episode characteristics for detailed explanations.

Following the aforementioned inclusion and exclusion criteria on HWIs and measurements of patient adverse outcomes, there were 10 studies that employed HWIs that were not extractable from hospital episode datasets and were further excluded from this review. There were finally 13 papers reviewed in this chapter. Figure 2.1 summarizes the inclusion and exclusion criteria employed for this review.

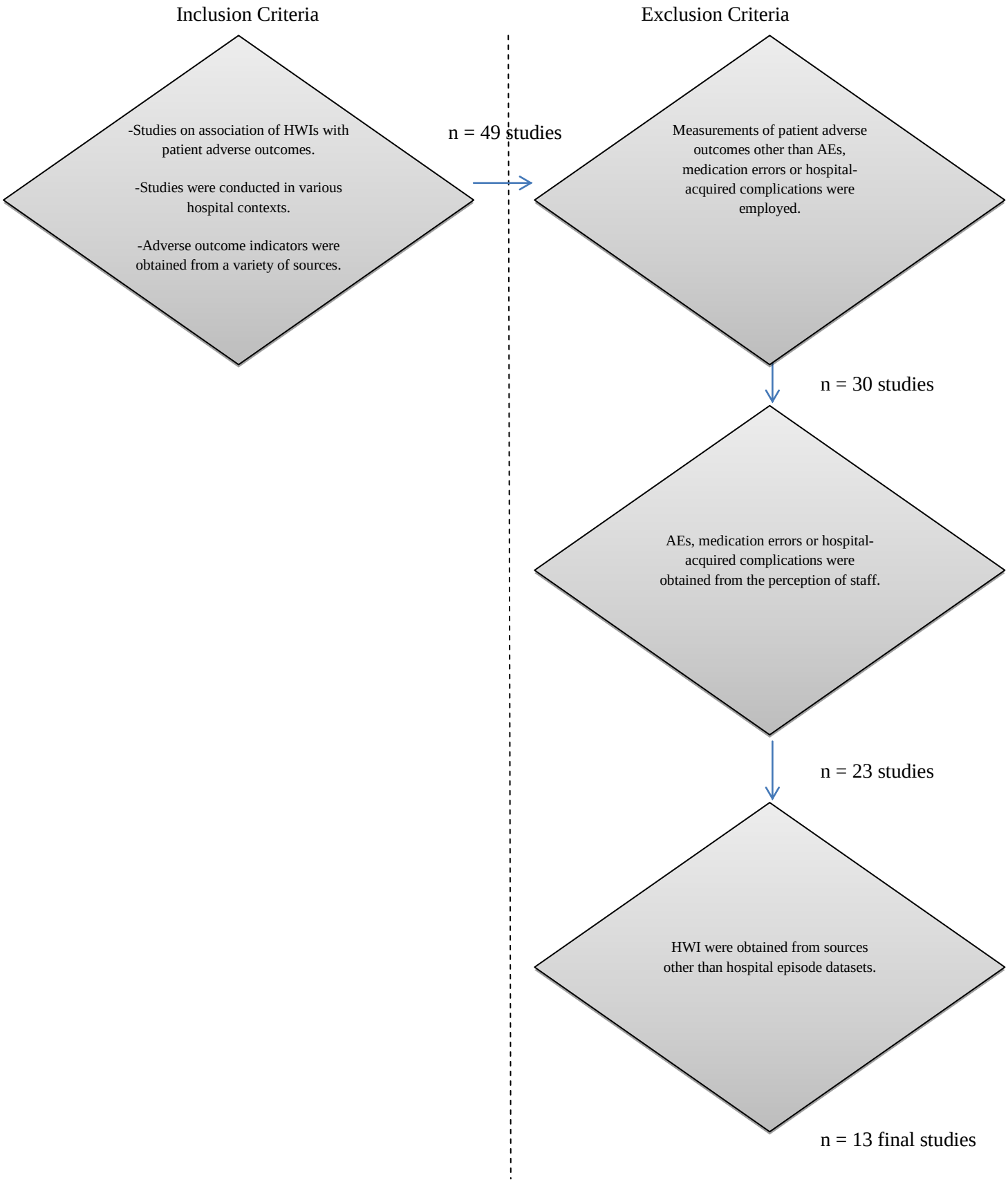

Figure 2.1 Summary of Inclusion and Exclusion Criteria for this Review.

2.3 Association of HWIs with AEs, Medication Errors and Hospital-Acquired Complications

In comparison to other studies (Epstein et al., 2012; Pedroja, 2008; Tibby et al., 2004) that investigated the association between HWIs and adverse outcomes (AEs, medication errors, hospital-acquired complications), Weissman et al. (2007) suggested a relatively comprehensive suite of HWIs in four dimensions (volume, throughput, patient complexity, nurse staffing and workload). The initial review of the literature revealed all HWIs that are extractable from hospital episode datasets (such as number of admissions, number of discharges, number of patients, patients' DRG cost weights), can be categorized into one of the dimensions of HWIs suggested by Weissman et al. (2007). It should be noted that different dimensions of HWIs can have varying effects on the likelihood of patients' adverse outcomes (Duffield et al., 2011; Weissman et al., 2007). Therefore, the following sections provide the evidence for the association between each dimension of HWIs with the likelihood of patients' AEs, medication errors and hospital-acquired complications.

2.3.1 Volume

Numerous studies have been conducted to examine the association between hospital volume indicators and the likelihood of patients' adverse outcomes such as AEs (Duffield et al., 2011; Epstein et al., 2012), medication errors (Duffield et al., 2011) or hospital-acquired complications (Pines et al., 2009; Zhou et al., 2012). These studies have been conducted in different departments within hospital settings such as: ICUs (Tibby et al., 2004; Tucker, Parry, McCabe, Nicolson, & Tarnow-Mordi, 2002); EDs (Epstein et al., 2012; Pines et al., 2009; Zhou et al., 2012); and general hospital units (wards) (Duffield et al., 2011); as well as entire hospitals (Pedroja, 2008; Pedroja, Blegen, Abravanel, Stromberg, & Spurlock, 2014).

In addition, studies on the association of hospital volume indicators with adverse outcomes have employed different units of analysis for establishing the relational (adjusted) models[18]. Different units of analysis have been employed for both volume indicators (input) and adverse outcomes (output) in the relational models. As a consequence of these different units of analysis, the association of HWIs with adverse outcomes has been examined differently in different scenarios. For example, some studies have examined the association of a patient's

[18] The term "adjusted model" can be used equivalently to denote the relational model. However, as it will be discussed, the adjusted models in the literature are not actually fully adjusted to include the effects all sufficient dimensions of HWIs (such as volume, throughput, nurse staffing and patient complexity) in the models.

exposure to hospital volume indicators with the likelihood of a patient's adverse outcomes (Epstein et al., 2012; Pines et al., 2009; Tucker et al., 2002). Others used a different unit of analysis and conducted the analysis on a daily basis. For example, some studies (Pedroja et al., 2014; Tibby et al., 2004) examined the association of daily rates of hospital or unit[19] volume indicators with daily rates of a hospital or unit's adverse outcomes. In contrast, Duffield et al. (2011) did not employ the volume indicators on a daily basis and instead, examined the association of unit (ward) volume indicators with the unit rates of adverse outcomes using an average measurement of volume and adverse outcomes in the unit.

Among studies investigating the interaction between volume and AEs, medication errors, or hospital-acquired complications, a relatively consistent association of higher volume indicators with increased likelihood of those adverse outcomes has been reported. This association was observed regardless of the study context, the type of volume indicators, or the employed units of analysis of volume indicators in the adjusted models[20].

The next subsections summarize the evidence from the literature for the association of hospital volume indicators with AEs, medication errors, or hospital-acquired complications based on the study contexts.

2.3.1.1 ICU

Within an ICU context, a study by Tibby et al. (2004) examined the association of hospital volume indicators with AEs and medication errors. A significant association between higher hospital volume indicators (represented by bed occupancy), and increased likelihood of patients' adverse outcomes (such as medication errors) was found. More precisely, Tibby et al. (2004) examined the association of ICU volume (bed occupancy)[21] per shift with the likelihood of an ICU's AE or medication error per shift. For this purpose, a longitudinal single-centre study was conducted, including 730 consecutive shifts in a UK hospital's Paediatric ICU (PICU) from 1st April 2001 to 31th March 2002. AEs included intravenous/arterial line equipment related injuries, medication errors, patient care misprocess, accidental extubation and other patient injuries (such as pressure sores, needle stick injuries).

[19] In this context, unit denotes all hospital departments other than the hospital itself; for example, an ICU, ED or ward.
[20] AEs, medication errors or hospital acquired complications are different concepts in my thesis. Only, if they result in a patient harm are considered as an AE. This main rational for separation of aforementioned outcomes
[21] In addition to volume, Tibby et al. (2004) examined the association of throughput (number of admissions and discharges) with the rate of AEs. This evidence will be provided in Section 2.3.2: Throughput.

The likelihood of an ICU's AE and medication error per shift was obtained from aggregated likelihoods of the ICU's individual patients' AEs and medication errors per shift. The incidents of AEs and medication errors were reported by staff and nurses through an incident (AE) reporting system. Tibby et al. (2004) found significant association between higher numbers of occupied beds on a shift with the increased likelihood of the shift's accidental extubation (*OR* = 1.26, *p* = .05, 95% CI [1.0, 1.59]). It is notable that Tibby et al. (2004) did not report a significant association of higher ICU volume with increased likelihood of occurrences of other types of AEs and medication errors. This demonstrates the covert relationship of HWIs with AEs and medication errors in which increased HWIs do not have a significant association with all types of AEs or medication errors, but may have a significant association with a particular type of AE or medication error.

However, this study by Tibby et al. (2004) has major limitations. The authors obtained an aggregated likelihood for occurrences of a shift's AE or medication error (using individual patients rates), however, there were no risk adjustments (inclusions) for the effect of the patient characteristic indicators (such as age, sex, existences of a comorbid condition or admission type) on the likelihood of an individual patient's AE or medication error.

It should be noted that in any adjusted model of HWIs with adverse outcomes, there is a need for risk adjustments of patient-level indicators to account for heterogeneity among patients (Iezzoni, 1997). An example of a risk adjustment process for the inclusion of the effect of individual patient characteristic indicators in the adjusted model was developed in a seminal study conducted by Needleman et al. (2002)[22]. The risk adjustment process employed a separated statistical model for the prediction of the likelihood of an individual patient's adverse outcome based on the individual's demographic characteristics (Needleman et al., 2002). Consequently, the aggregated rates or likelihood of adverse outcomes were obtained from the predicted values of adverse outcomes based on the employed statistical model rather than the real and observed values (Needleman et al., 2002). These predicted values are then used in the final HWI statistical model. This process ensures the effect of individual patient characteristics is included in the adjusted model of HWIs with adverse outcomes.

[22] Needleman et al. (2002) conducted a multi-centre study to examine the association of hospital nurse staffing on a variety of patient adverse outcomes including LOS, death and AEs. However, this study was excluded from this review since the employed measurement of nurse staffing was not extractable from hospital episode dataset (refer to Section 2.2.2: HWIs).

It should be taken into consideration that, from a statistical point of view, if patient characteristic indicators have a significant effect on adverse outcomes and they are neglected in the adjusted model, the association of HWIs with adverse outcomes could be biased due to omitted variable bias effect (Barreto & Frank, 2005). The omitted variable bias effect occurs when the adjusted model compensates for the significant effect of a missing indicator by either underestimation or overestimation of other independent indicators (Barreto & ,knarF 2005). In this context the missing indicator is patient characteristics, which can lead to an incorrect estimation for the effect of other independent indicators such as HWIs on adverse outcomes.

While Tibby et al. (2004) found a significant association of higher hospital volume with an increased likelihood of patients' adverse outcomes such as medication errors, Tucker et al. (2002) reported no such association for infants' complications. A longitudinal retrospective multi-centre study, including 13,515 infants admitted to 54 randomly selected UK neonatal ICUs (NICUs) between March 1998 and April 1999 was conducted. Tucker et al. (2002) examined the association between ICU volume (occupancy) and the likelihood of an infant's complication[23]. The volume was calculated as either the average of daily ICU occupancy values during the entire infant's LOS (average measurement) or ICU occupancy on the first day of an infant's stay (first day measurement). The infant's complication was acquired during hospitalisation and was obtained using chart reviews of the patients' medical records. These complications included major cerebral abnormality of probable postnatal origin (cystic leucomalacia or porencephalic cyst on cranial ultrasound arising more than 10 days after birth), and probable nosocomial bacteraemia (first positive blood culture more than 48 hours after birth). No significant association of higher ICU volume with the increased likelihood of an infant's complication was reported. Similarly, no significant association was discovered by using either the average measurement of HWIs or by using first day measurement of HWIs. Although the authors did not report any significant association; it is quite possible higher values of volume indicators, above a tipping point (for example, when volume indicators have an intensified value), would be significantly associated with an increased likelihood of an infant's complication. This view has been supported by some other studies (Kuntz et al., 2011, 2014) on the association of higher hospital volume indicators above a tipping point, with an

[23] It is notable that Tibby et al. (2004) examined the association of shift ICU volume indicators with shift aggregated rates of AEs and medication errors, while Tucker et al. (2002) examined the association of infant exposure to ICU volume with the likelihood of an infant's complication (refer to Section 2.3.1: Volume).

increased likelihood of a patient's in-hospital mortality. This could be quite possible for hospital acquired complications and AEs as well. Therefore, if the authors used the concept of tipping point for measuring the hospital volume indicator (bed occupancy), perhaps they could demonstrate a significant association of higher volume with increased likelihood of an infant complication when volume has an intensified value. The main limitation associated with the study by Tucker et al. (2002) is that the authors only employed two complications (major cerebral abnormality of probable postnatal origin and probable nosocomial bacteraemia) in their investigation. This could also explain why Tucker et al. (2002) did not obtain a significant association of higher volume indicators with an increased likelihood of an infants' complication. In contrast, while this thesis does not aim to identify complications, it employs the CHADx, which includes at least 74 diagnoses related to infants and newborns' complications (ACSQHC, 2013). These complications are related to the CHADx 13 major category (perinatal complications) and are then used to identify the possible infants' AEs.

2.3.1.2 ED

In a different context to Tibby et al. (2004), but supporting their results, three studies within an ED context indicated the association of higher volume with an increased likelihood of a patient's AE (Epstein et al., 2012) and a hospital-acquired complication (Pines et al., 2009; Zhou et al., 2012). Pines et al. (2009) conducted a retrospective longitudinal single-centre study with a cohort of 4,574 patients between 1999 and 2006 who were admitted to the ED of a large urban teaching hospital in Pennsylvania, USA. The cohort was divided into 803 patients with acute coronary syndromes (ACS) and 3,372 patients with non-ACS related syndromes. Pines et al. (2009) examined the association of ED occupancy[24] at the time of patient triage (admission to an ED) with the likelihood of a patient's adverse cardiovascular outcome acquired in the ED. The patient's adverse cardiovascular outcome included occurrences of cardiac arrest, delayed myocardial infarction, heart failure, dysrhythmias or hypotension during hospitalisation[25]. These adverse outcomes were obtained from the chart review of the patients' medical records. Pines et al. (2009) concluded that in patients with ACS, higher occupancy (above the 75th percentile) at the time of patient triage was associated with increased likelihood of an adverse cardiovascular outcome (*OR* = 3.1, 95% CI [1.0, 9.3]).

[24] In addition to ED volume (occupancy), Pines et al. (2009) examined the association of an ED throughput (number of admissions) with the likelihood of patient cardiovascular outcomes (refer to Section 2.3.2: Throughput).

[25] It is notable that authors have also considered rate of death as part of patient adverse outcomes. However, the frequency of death in the employed cohort was zero (Pines et al., 2009, Table 2).

There is a major limitation associated with the design of the study conducted by Pines et al. (2009). The employed model was not fully adjusted for the effects of other dimensions of HWIs such as throughput, patient complexity, and nurse staffing. Therefore, the indicated association of higher volume with increased likelihood of a patient's cardiovascular outcome may be spurious.

A spurious association occurs when two HWIs (independent indicators) are positively correlated with each other while only one of them (the effective indicator) is associated with the increased likelihood of the adverse outcome indicator (dependent indicator). In this case, when the study design omits the interaction of effective HWI with adverse outcomes, a spurious association between the ineffective HWI and adverse outcome may be obtained. HWIs can be inter-correlated with each other even if they are within different dimensions, and it is essential for a robust design to consider all potential confounding variables. This is necessary to avoid any over or underestimated effects due to the use of an unadjusted model.

For example, considering an AE as an adverse outcome indicator (this applies to any other possible adverse outcome indicator as well), in the case where the number of admissions has a genuine and stronger association with increased likelihood of AEs, bed occupancy is likely to be increased by the higher numbers of admissions as well. However, if the number of admissions is omitted from the model, bed occupancy would have a spurious and overestimated association with increased likelihood of a patient's AE (See Figure 2.2). Another example would be the effect of number of admission or discharges on both increased likelihood of AEs and hospital patients complexity. There could be a case, whereby increased admissions of more severely unwell patients (or equivalently, increased discharges of less seriously unwell patients), the hospital patients' complexity would be increased. Furthermore, higher number of admissions (and discharges) could increase the likelihood of a patient's AE (Weissman et al., 2007). Thus, in the absence of number of admissions (or discharges) in an adjusted model, higher hospital patient complexity could represent a spurious and overestimated association with increased likelihood of a patient's AE[26]. In contrast to Pines et al. (2009), the existence of spurious associations is explicitly addressed in the design of this

[26] This drawback is very evident in the study by Weissman et al. (2007) as the authors use separate models for establishing adjusted models HWIs with AEs to represent the association of each HWI with AEs. The detailed information regarding this study is provided in the Section 2.3.1.4: Hospital.

thesis by inclusion of sufficient numbers of HWIs in the employed adjusted models and then validation of them to reach a desirable amount of accuracy.

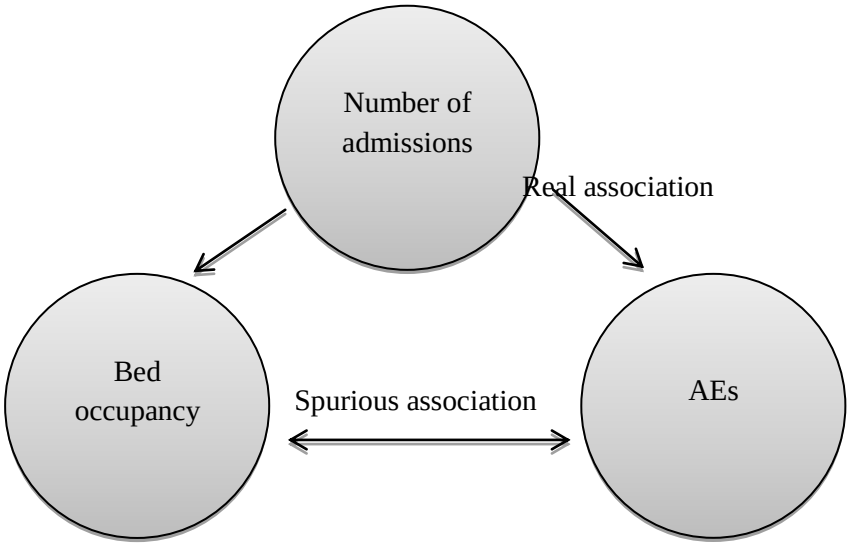

Figure 2.2 Spurious Association Between Bed Occupancy (Ineffective Indicator) and AEs in the Absence of Number of Admissions (an Effective Indicator).

In another US study, Epstein et al. (2012) conducted a retrospective multi-centre study including a sample of 533 ED infants within four EDs in Massachusetts (USA) in 2004. The samples were confined to infants having a principal diagnosis of acute myocardial infarction (AMI), asthma exacerbation and dislocation. The authors examined the association of the ED overcrowding measurements during the infant's stay with the likelihood of an infant's preventable medical error (PME). The ED overcrowding measurement was established using the average of ED occupancy for each ten minutes during the infant's LOS. A PME was considered as an injury (AE) resulting from a medical error and obtained by using a chart review of the infant's medical records[27]. Epstein et al. (2012) found a significant association between higher average daily ED overcrowding measurements (quartile 4 vs 1), and an increased likelihood of an infant's PME (*OR* = 2.28, 95% CI [1.19, 4.38]). It is notable that there are numerous limitations associated with this study. Firstly, the authors did not adjust the model by incorporating some effective patient characteristic indicators, such as comorbid conditions and admission type. It has been proven these patient characteristic indicators

[27] Some examples of PMEs are: duplicate prescription or usage of drugs, missing physician notes, administering high dosage of drugs, prescription of drugs with adverse effect on patients. For a complete list of PMEs, readers should refer to the study by Epstein's et al. (2012).

significantly affect the likelihood of a patient's AE (Bohensky et al., 2013; Miyata, Motomura, Yozu, Kyo, & Takamoto, 2011). Secondly, not all dimensions of HWIs such as throughput, patient complexity, and nurse staffing were employed in the adjusted model. As explained previously, this can lead to a spurious or overestimated association between ED overcrowding measurements and the likelihood of a PME[28].

In the largest ED context study based on the study sample among the reviewed studies, Zhou et al. (2012) conducted a retrospective single-centre study involving 20,276 ED admission patients, within a Chinese teaching hospital, from 1st January 2006 to 31th December 2009. The authors investigated the relationship between daily hospital bed occupancy[29] and the frequency of serious complications in the ED for each day during the study period. Serious complications, such as new onset shock, and the need for intubation were identified using chart reviews of patients' medical records. A strong association between higher hospital bed occupancy and frequency of new onset shock was reported (frequency per 1,000 patient days for occupancy > 95% vs occupancy < 90% = 11.65 vs 7.87, p = .062). Likewise, a significant association between higher hospital bed occupancy and higher frequencies of the need for intubation (frequency per 1,000 patient days for occupancy > 95% vs occupancy < 90% = 9.55 vs 4.54, p = .005) was also found (Zhou et al., 2012).

The main limitation of the study by Zhou et al. (2012) is that the aforementioned associations were reported based on an unadjusted model. The study design did not take into the account the effect of other dimensions of HWIs such as patient complexity and nurse staffing. Therefore, the results may represent a spurious association between bed occupancy and AEs. Moreover, and similar to Tibby et al. (2004), Zhou et al. (2012) did not employ a risk adjustment process to include the effect of patient characteristics while obtaining the aggregate rates of adverse outcomes (cardiovascular complications) for each day. Neglecting patient characteristic indicators can make the adjusted model of HWIs with cardiovascular complications unreliable due to the omitted variable bias effect (Barreto & Frank, 2005).

[28] In the literature, Weismann's study is the only study which has used a comprehensive suite of HWIs with sufficient numbers of dimensions.

[29] Zhou et al. (2012) have also looked at the relationship of ED throughput (number of admissions) with the likehood of serious complication. This association will be discussed in Section 2.3.2: Throughput.

2.3.1.3 Ward

Similar to the results reported by Tibby et al. (2004) on the associations of higher ICU volume indicators with an increased likelihood of a patient's medication error, Duffield et al. (2011) found a similar association within wards. However, Duffield et al. (2011) employed a different design and examined the association of a ward's volume with the ward's rate of patient medication errors, AEs, and hospital-acquired complications. This is in contrast to Tibby et al. (2004) who examined the association of daily rates of ICU volume indicators with daily rates of ICU AEs and medication errors. Duffield et al. (2011) conducted a large-scale longitudinal and cross-sectional study. The association of ward volume with ward rates of AEs, medication errors and hospital-acquired complications was examined in the cross-sectional component of the study. This component consisted of 80 hospital units with 5,885 patients from 19 hospitals in NSW, Australia. Ward volume was measured as the average of the ward's daily occupancies during the study period. Ward rate of AEs, medication errors and hospital-acquired complications were obtained from the individual counts of those events for all the patients in each ward. The authors employed FTR and falls as measurements of AEs. Hospital-acquired complications were represented by outcomes potentially sensitive to nursing (OPSN). Medication errors were all non-time-based (typical) or time-based medication errors (medication given more than 30 minutes after prescription time). These events were either obtained from the hospitals' incident management reporting systems or hospital episode datasets. For example, OPSNs were obtained from hospital episode datasets including eleven acquired complications during hospitalisation, such as urinary tract infection (UTI), decubiti, pneumonia, deep vein thrombosis, ulcer/GI bleeding, central nervous system complications (CNS), sepsis, shock/cardiac arrest, surgical wound infection, pulmonary failure and physiological/metabolic derangement. Separate analyses were conducted for each type of patients' AEs, medication errors and hospital-acquired complications. It was found that wards with higher occupancies faced significantly higher time-based medication errors (*Rate Ratio (RR)* = 2.20, $p \leq .01$). No significant association was reported for other types of AEs, medication errors or hospital-acquired complications ($p \geq .05$). These findings reinforce the covert association of hospital volume indicators with adverse outcomes, as identified by Tibby et al. (2004) where the association was significant for a particular type of event. Moreover, similar to Tibby et al. (2004) and Zhou et al. (2012), Duffield et al. (2011) did not employ a risk adjustment process to include the effect of patient characteristics in an estimation of a ward's rates of adverse outcomes. Once again, the neglected effect of patient

characteristic indicators can create an omitted variable bias effect (Barreto & Frank, 2005) between volume and medication errors.

Furthermore, this study by Duffield et al. (2011) was conducted within a multi-centre environment across several hospitals and hospital wards. It is likely that the effect of HWIs on adverse outcomes could vary enormously between individual hospitals and wards. These variations could be due to different hospital or hospital ward characteristics, some of which may not be observable (Van den Heede et al., 2009). It is notable that, in econometrics, the result of an adjusted model may be erroneous, when, in addition to the observed variables, there exist other unobserved characteristics, which are correlated with the observed variables (Arellano, 2003). An example of the unobservable characteristics could be difference in hospital policies that are set by the hospital authorities (Van den Heede et al., 2009). This phenomenon is referred to as the random effect of HWIs on adverse outcomes. Moreover, the random effect of HWIs on patient adverse outcomes could emerge within different types of patients. For example, Berry Jaeker & Tucker (2012a) showed that the effect of HWIs on patients' LOS could vary among patients within different DRGs. Similarly, these differences could occur if AEs, medication errors or hospital-acquired complications were selected as the outcome variable. It is notable the random effect mainly emerges due to immeasurable (unobservable) characteristics of hospitals or patients, which cannot be explicitly employed in the adjusted model. In other words, there is no definite metric to measure the random effects and employ them in the conceptual framework. For example, patients' different moods or perceptions could affect the likelihood of a patient's AE, but no clear metric exists to measure these.

According to the omitted variable bias effect (Barreto & Frank, 2005), neglecting the random effect in the adjusted model of HWIs with adverse outcomes could further undermine the accuracy of the model, if the random effect had a significant effect on the adverse outcome indicator. The significance of the random effect in an adjusted model of HWIs with adverse outcomes would suggest there are significant unobserved effects, which further affect the likelihood of patients' adverse outcomes. In contrast to Duffield et al. (2011), this thesis includes the random effects of HWIs within patients' adjacent DRGs to include all unobserved effects due to heterogeneity between patients as been neglected from the conceptual model. However, since the study was conducted in a single hospital no such effect was included for the unobservable effects due to heterogeneity of hospital characteristics for

the patients treated in different hospitals. Similar to hospitals, no such effects was implemented at unit or ward level due to nonexistence of any indicator representing the patient's hospitalized ward or unit in the employed dataset of this thesis.

2.3.1.4 Hospital

In concert with Epstein et al. (2012) on the association of higher volume indicators with the increased likelihood of a patients' AE, three studies within a hospital context (Pedroja, 2008; Pedroja et al., 2014; Weissman et al., 2007) indicated a similar association. In a similar design to Tibby et al. (2004) and Zhou et al. (2012), Pedroja (2008) examined the association of daily HWIs with daily rates of hospital-acquired patient harm (AEs). For this purpose, the authors undertook a longitudinal analysis of 515 days within two Californian (USA) hospitals. Pedroja (2008)[30] employed five measurements of daily HWIs, including total inpatient census at midnight, number of surgeries (scheduled and unscheduled), number of add-ons (unscheduled surgeries), percentage of add-ons, and number of behavioural health admissions from ED. A daily composite index of HWIs including the volume dimension (bed occupancy)[31] was constructed based on the number of HWIs having intensified values each day (*Z-score* ≥ 1.5). Pedroja (2008) examined the association of daily HWIs with daily rates of hospital patient harm. These harms included minor and major injuries and death, which were obtained from the hospital incident management reporting system. Pedroja (2008) found the days with a higher percentage of hospital patient harms coincided with days when a higher percentage of HWIs had intensified values. The main drawback associated with this study is that the results were not adjusted for the effects of other dimensions of HWIs such as patient complexity or nurse staffing. Therefore, the results can represent a spurious association between occupancy and AEs. Moreover, and similar to Tibby et al. (2004), Zhou et al. (2012), and Duffield et al. (2011), the aggregated rates of patient harms for each day was not obtained by using a risk-adjustment process to include the effect of individual patient characteristic indicators, creating an omitted variable bias effect of patient characteristics (Barreto & Frank, 2005) which may lead to misleading results.

In a subsequent study, Pedroja et al. (2014) conducted a longitudinal analysis of 365 days (260 weekdays and 105 weekend days) within two Californian hospitals. The authors

[30] The unit of analysis of AEs in this study is hospital rates of AEs per day.
[31] This workload index includes two dimensions of HWIs including volume (total inpatient census at midnight) and throughput (number of behavioural health admissions).

examined the association of daily hospital system load (HSL) with daily rates of hospital patient harm. The HSL was acquired from a wide range of HWIs[32] using factor analysis for both weekdays and weekends. The Operating Room (OR) and patient census indicators[33] were the principal HSL indicators explaining 24% of the overall variance for all week and weekend days. Daily hospital patient harm was obtained using a scoring value based on the sum of square values of the injury scores for each patient based on the level of injury (0 = unable to determine, 1 = no harm, not reached patient, 2 = no harm, reached the patient, 3 = reached the patient with minimal harm, 4 = moderate harm, 5 = serious harm, 6 = death). Both HSL indicators and patient harms were extracted from hospital episode datasets and hospital incident management reporting systems. Pedroja et al. (2014) reported a significant association between higher numbers of HSL indicators in the top quartile (above 75% percentile) in each day and an increased daily hospital harm score. This relationship was observed across the two hospitals on both weekdays and weekends (first hospital: weekdays - *Pearson correlation (r)* = .229, $p < .05$, first hospital: weekends - $r = .238$, $p < .05$, second hospital: weekdays - $r = .127$, $p < .05$, second hospital: weekends - $r = .250$, $p <. 05$) (Pedroja et al., 2014). Similar to the previous study (Pedroja, 2008), the main limitation associated with this study is that the above results were not adjusted for the effects of other dimensions of HWIs such as patient complexity or nurse staffing. Again, no risk adjustment process, to include the effect of patient characteristics in the adjusted model of HWIs with AEs, was employed making the model susceptible to omitted variable bias effect (Barreto & Frank, 2005).

In a slightly different design to the above studies by Pedroja (2008) and Pedroja et al. (2014) (in which the association of daily hospital or unit volume indicators with daily hospital AEs was observed), Weissman et al. (2007) examined the association of the daily hospital volume indicator (hospital bed occupancy)[34] with the frequency of a patient's AE per day[35]. For this purpose, a retrospective longitudinal study, including a sample of 24,676 discharge records

[32] For detailed information regarding the list of these indicators, it is suggested that readers refer to the original study.
[33] This includes number of patients (bed occupancy), OR occupancy, numbers of minutes in OR, and all transfers within units.
[34] In addition to volume indicators, Weissman et al. (2007) examined the association of throughput (number of admissions, number of discharges), nurse staffing (patient to nurse ratio) and patient complexity (patients' DRG weights) with the likelihood of patient's AEs per day. These associations are provided in Section 2.3.3: Patient complexity.
[35] In contrast to other studies in this section, the unit of analysis of AEs in Weissman's et al. (2007) study is patient per day; thus, the association of HWIs with the likelihood of patient's AEs per day was examined.

from four US hospitals between October 2000 and September 2001 was conducted. AEs were obtained by chart review of the patients' medical records. In just one of the four hospitals, Weissman et al. (2007) found a significant association of higher daily hospital occupancy with increased frequency of a patient's AE per day (β = 2.50, p < .001). There are numerous limitations associated with this study. Firstly, Weissman et al. (2007) found a significant association of higher volume indicators with increased frequency of a patient's AE for only one of the four hospitals examined in the study. Secondly, and more importantly, since the unit of analysis of AEs is 'patient per day', AEs should be estimated for each day during the patient's LOS. This is subject to inaccuracy as the exact time (or the day) of occurrences of AEs during the patient's LOS is not always evident (Weissman et al., 2007). Thirdly, it has been proven that the existence of a comorbid condition has significant association with the increased likelihood of a patient's AE (Bohensky et al., 2013). Weissman et al. (2007) did not take into account the effect of comorbid conditions in their adjusted model. This could result in an overestimated association of HWIs with AEs, if the presence of a comorbid condition had a significant effect on the increased likelihood of a patient's AE. In addition, although Weissman et al. (2007) proposed a comprehensive suite of HWIs, they employed separated models for each HWI. Therefore the models are not fully adjusted for the effect of other HWIs, which can lead to a spurious or overestimated association.

2.3.1.5 Summary

Summarising the results of the reviewed literature, the majority of studies (all reviewed studies except Tucker et al. (2002)) indicated a significant association of higher volume indicators with increased likelihood of at least one type of patients' adverse outcomes such as AEs, medication errors or hospital-acquired complications. These associations were observed in different hospital departments (contexts) using different measurements of hospital volume indicators. Tables 2.1, 2.2, and 2.3 summarise these associations.

Table 2.1

Association of Hospital Volume Indicators Using Average Measurement with the Likelihood of a Patient's' AE, Medication Error and Hospital-Acquired Complication.

Authors	**Context of study**	**Study design**	**Measurement of patient adverse outcomes**	**Measurement of hospital volume indicators**	**Association**
Epstein et al. (2012)	ED	Retrospective longitudinal multi-centre	Preventable Medical Errors (PME)- (AE injuries)	Average of ED overcrowding measurement (using bed occupancy) for each ten minutes during the patient's LOS	↑occupancy ⇒ ↑PME¶
Tucker et al. (2002)	ICU	Retrospective longitudinal multi-centre	Perinatal complications	Average of daily ICU volume during the patient's LOS	↑occupancy ≠ ↑perinatal complications‖

Note. ¶ *The legend* $\uparrow x \Rightarrow \uparrow y$ *means there is significant association between higher values of x and increased likelihood of y.*

‖ *The legend* $\uparrow x \neq \uparrow y$ *means there is no significant association between higher values of x and increased likelihood of y.*

Table 2.2

Association of Hospital Volume Indicators Using First Day Measurement with the Likelihood of a Patient's AE, Medication Error and Hospital-Acquired Complication.

Authors	**Context of study**	**Study design**	**Measurement of patient adverse outcomes**	**Measurement of hospital volume indicators**	**Association**
Pines et al. (2009)	ED	Retrospective longitudinal single-centre	Adverse cardiovascular outcomes	ED occupancy at the time of admission	↑occupancy ⇒ ↑adverse cardiovascular outcomes¶
Tucker et al. (2002)	ICU	Retrospective longitudinal multi-centre	Perinatal complications	ICU occupancy at the time of admission	↑occupancy ≠ ↑ perinatal complications‖

Note. ¶ *The legend* $\uparrow x \Rightarrow \uparrow y$ *means there is significant association between higher values of x and increased likelihood of y.*

‖ *The legend* $\uparrow x \neq \uparrow y$ *means there is no significant association between higher values of x and increased likelihood of y*

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Table 2.3

Association of Hospital Volume Iindicators with the Likelihood of Patients' AEs, Medication Errors and Hospital-Acquired Complications (Using Measurements other than Average and First Day Measurements).

Authors	Context of study	Study design	Measurement of patient adverse outcomes	Measurement of hospital volume indicators	Association
Pedroja (2008)	Hospital	Retrospective longitudinal multi-centre	Daily rates of hospital's patients' harms (AEs)	DHWIs (a composite index of HWIs including bed occupancy)	↑composite index of HWIs ⇒ ↑patient harms¶
Pedroja et al. (2014)	Hospital	Retrospective longitudinal multi-centre	Daily rates of hospital's patients' harms (AEs)	Daily hospital system load (HSL)[36]	↑HSL ⇒ ↑patient harms
Tibby et al. (2004)	ICU	Retrospective longitudinal single-centre	Daily rates of ICU's complications	DHWIs on ICU's	↑occupancy ⇒ ↑accidental extubation
Zhou et al. (2012)	ED	Retrospective longitudinal	Daily ED serious	Daily hospital occupancy	↑hospital occupancy ⇒ ↑complications

[36] The majority of this indicator (24% of overall variance) was explained by OR and hospital census.

		single-centre	complications		
Weissman et al. (2007)	Hospital	Retrospective longitudinal multi-centre	Frequency of a patient's AE per day	Daily hospital bed occupancy	↑occupancy ⇒ ↑AEs
Duffield et al. (2011)	Hospital units	Retrospective cross sectional multi-centre	Ward's untoward events (OPSN, medication errors, falls, FTRs)	Ward's occupancy (average of daily ward's occupancies during the study period)	↑occupancy ⇒ ↑medication errors

Note. ¶ The legend ↑x ⇒ ↑y means there is significant association between higher values of x and increased likelihood of y.

As shown in Table 2.1, in two studies that employed an average measurement of hospital volume indicators, Epstein et al. (2012) found a significant association of higher volume indicators with increased likelihood of a patient's adverse outcomes such as AE, while Tucker et al. (2002) did not obtain this significant association for infants' complications. In addition, when the measurement of hospital volume indicators at the time of admission was employed (Table 2.2), Pines et al. (2009) found a significant association of higher volume indicators with the increased likelihood of a patient's hospital-acquired complications. In contrast, Tucker et al. (2002) failed to find any such effect on infants' complications, although this may have been due to the very narrow range of complications considered. Moreover, all studies that employed measurements of hospital volume indicators other than average or first day measurements (Table 2.3) found significant associations of higher volume indicators with increased likelihood of a patients' adverse outcomes, such as AEs (Pedroja, 2008; Pedroja et al., 2014; Weissman et al., 2007), medication errors (Duffield et al., 2011; Tibby et al., 2004) and hospital-acquired complications (Zhou et al., 2012). All the above associations (Tables 2.1, 2.2, and 2.3) were shown by using different measurements of hospital volume indicators, and were observed within different study contexts, which further affirms the consistency of the aforementioned trend with the volume dimension of HWIs.

Overall, results suggest that higher hospital volume indicators are associated with increased rates of patients' adverse outcomes such as medication errors or and consequent hospital-acquired complications and AEs. This further confirms our previous assumptions in this review (refer to Section 2.2.1: Adverse outcomes) that volume can increase the rate of medication errors leading to higher rates of hospital acquired complications and AEs (de Vries, Ramrattan, Smorenburg, Gouma, & Boermeester, 2008; Jagsi et al., 2005; Wilson et al., 1999).

2.3.2 Throughput

Throughput or turnover refers to the rate at which patients are transferred or discharged from the hospital. Weissman et al. (2007) measured the throughput dimension of HWIs using the number of admissions and discharges. In comparison to volume, as discussed in the previous section, fewer studies have concentrated on the association of throughput indicators with the likelihood of patients' adverse outcomes. These studies did not obtain a significant association of higher throughput indicators with increased likelihood of patients' adverse outcomes such as AEs (Duffield et al., 2011; Evans & Kim, 2006; Tibby et al., 2004), medication errors

(Duffield et al., 2011; Tibby et al., 2004) or hospital-acquired complications (Pines et al., 2009; Zhou et al., 2012). Evans and Kim (2006) conducted a retrospective longitudinal multi-centre study including a sample of 48,223 patients in 397 Californian hospitals between 1996 and 2000. These patients had complications such as pneumonia, deep vein thrombosis/pulmonary embolism, sepsis, acute renal failure, shock/cardiac arrest, and gastrointestinal haemorrhage/acute ulcer. The authors examined the association of a hospital's number of admissions (within the second and third days of a patient's admission date) with the likelihood of a patient's FTR (AE). FTR was identified as death following the above complications. No association was found between higher hospital numbers of admissions on the second and third day of the patient's admission date with an increased likelihood of a patient's FTR (β = -.0077, *Standard Error (SE)* = .0078)[37] (Evans & Kim, 2006). It is notable that similar to Duffield et al. (2011), while Evans and Kim (2006) conducted the study in a multi-centre context, they did not include the random effect of HWIs on AEs due to unobservable and heterogeneous characteristics between different hospitals. This could lead to an unreliable result if this random effect had significant effect on AEs (omitted variable bias effect).

Moreover, Pines et al. (2009) did not find a significant association between higher ED throughput (number of admissions) at the time of the patient's admission, with an increased likelihood of a patient's hospital-acquired complication (represented by hospital-acquired cardiovascular adverse outcomes) (*OR* = 1.6, $p > .05$, 95% CI [.6, 4.1]). Likewise, Weissman et al. (2007) did not obtain a significant association between higher numbers of admissions (β = .008, $p < .001$) and discharge (β = .008, $p < .001$) with increased frequencies of patients' AEs per day[38]. Interestingly, in a converse association, Tibby et al. (2004) found a higher daily number of admissions and discharges was associated with decreased daily rates of injuries (AEs) in a paediatric ICU (*OR* = .74, $p < .05$, 95% CI [.56, .97]). In addition, Duffield et al. (2011) found hospital wards with a higher proportion of planned admissions were associated with significantly reduced rates of medication errors (except time-based medication errors) (*RR* = -.84, $p < .01$). It is notable that this view was also supported for decreased rates of other measurements of patient adverse outcomes such as LOS. Berry Jaeker and Tucker (2012b) found that patient exposure to a higher load of predictable admissions (scheduled

[37] *B* values in above association have a very small negative value, which implies the association is insignificant (Evans & Kim, 2006).

[38] In the above association while *p* values indicated a significant value ($p < .001$), the β coefficients are very small; therefore, the associations were considered to be weak and insignificant.

admissions versus emergency admission) resulted in a lower patient's LOS (average LOS differences: .45 days, *t-value*: 8.31, $p < .001$). Table 2.4 summarises the aforementioned results.

Table 2.4

Association of Throughput Indicators with the Likelihood of Patients' AEs, Medication Errors and Hospital-Acquired Complications.

Authors	**Context of study**	**Study design**	**Measurement of patient adverse outcomes**	**Measurement of hospital throughput indicators**	**Association**
Pines et al. (2009)	ED	Retrospective longitudinal single-centre	Likelihood of a patient's adverse cardiovascular outcome.	Number of ED admissions at the time of patient's admission.	↑number of admissions ≠↑adverse cardiovascular outcomes¶
Evans and Kim (2006)	Hospital	Retrospective longitudinal multi-centre	Likelihood of a patient's FTR.	Hospital numbers of admissions within the second and third days of patient's admission date.	↑numbers of admissions ≠ ↑FTR
Weissman et al. (2007)	Hospital	Retrospective longitudinal multi-centre	Frequency of a patient's AE per day	Daily hospital numbers of admission and discharges	↑numbers of admissions and discharges ≠ ↑AEs
Tibby et al. (2004)	Paediatric ICU	Retrospective longitudinal single-centre	ICU daily rates of patient injuries and	ICU daily number of admission and discharges.	↑number of admission and discharges⇒ ↓PICU's injuries¦

			human errors.		
Duffield et al. (2011)	Hospital units	Retrospective cross sectional multi-centre	Ward's untoward events (OPSN, medication errors, FTR, falls).	Proportion of unit's planned admissions.	↑ proportion of ward's planned admissions ⇒↓medication errors (except time-based medication errors)

Note. ¶ *The legend* $\uparrow x \neq \uparrow y$ *means there is no significant association between higher values of x and increased likelihood of y.*

¦ *The legend* $\uparrow x \Rightarrow \downarrow y$ *means there is significant association between higher values of x and decreased likelihood of y.*

As shown in the studies summarised in Table 2.4, there is no significant association of higher throughput indicators with increased likelihood of patients' AEs, medication errors or hospital-acquired complications. This lack of association was observed regardless of study contexts or measurements of throughput indicators.

2.3.3 Patient complexity

Patient complexity, referring to the exposure to hospital patients' case complexities or the severities of the illness, is regarded as one of the dimensions of HWIs (Aiken et al., 2002; Estabrooks, Midodzi, Cummings, Ricker, & Giovannetti, 2005; Unruh, 2003). To the knowledge of the researcher, and according to the scope of this review (refer to Section 2.2: Inclusion and Exclusion Criteria), only Weissman et al. (2007) examined the association of the patient complexity dimension of HWIs with AEs, medication errors or hospital-acquired complications.

Weissman et al. (2007) employed patients' DRG cost weights for measuring the hospital patient complexity, linking it to AEs. No significant association between exposure to higher hospital patient complexity and increased likelihood of a patient's AE was found ($\beta < .0001$, $p > .05$). This insignificant association was also reported for other measurements of patient adverse outcomes in the literature such as in-hospital mortality (Kuntz et al., 2011), which were beyond of the scope of this review.

Since only Weissman et al. (2007) examined the association of the patient complexity dimension of HWIs with the likelihood of a patient's AE, no firm conclusion can be derived for this dimension of HWIs, but based on the fact the study was unable to find any significant association, it is possible that exposure to patient complexity plays only a minor role in the occurrences of AEs.

2.3.4 Nurse staffing and workload

Nurse staffing and workload is one of the dimensions of HWIs expected to have a crucial effect on the likelihood of patients' AEs (Weissman et al., 2007). Measurements of nurse staffing and workload have been employed extensively within the literature to examine their associations with AEs. As stated previously (refer to Section 2.2.2: HWIs), the literature conclusively showed a significant association of higher contribution of nurses or skilled staff with decreased likelihood of patients' adverse outcomes such as AEs (Kovner et al., 2002;

Unruh, 2003; Weissman et al., 2007). However, based on the scope of this review (refer to Section 2.2: Inclusion and Exclusion Criteria), no study was identified that extracted these indicators from hospital episode datasets.

2.4 Limitations

The literature on the association of HWIs with adverse outcomes such as AEs, medication errors or hospital-acquired complications has numerous limitations. First and foremost, most studies (Epstein et al., 2012; Evans & Kim, 2006; Pines et al., 2009; Zhou et al., 2012) failed to incorporate comprehensive suites of HWIs with sufficient numbers of dimensions. From a statistical point of view, this can lead to a biased conclusion about the association between HWIs and adverse outcomes.

Secondly, considering AEs as the measurement of patient adverse outcomes, some studies (Duffield et al., 2011; Pedroja et al., 2014; Tibby et al., 2004; Weissman et al., 2007) did not include the effect of patient characteristic indicators while establishing an adjusted model of HWIs with AEs. This was more evident in studies that used the aggregated rates of AEs, either in hospitals (Pedroja, 2008; Pedroja et al., 2014) or hospital units (Duffield et al., 2011; Tibby et al., 2004). As patients with different demographic characteristics have varying likelihood of AEs (Bohensky et al., 2013), from a statistical point of view, neglecting the effect of patient characteristics in an adjusted model of HWIs with AEs (lack of risk adjustment process for the effect of patient characteristic indicators) can lead to unreliable results particularly if they have significant effect on the likelihood of AEs (omitted variable bias effect). This is another reason that this thesis examines the association of HWIs with AEs at patient level. The association of HWIs with AEs at the patient level is obtained by examining the association of patient exposure to HWIs with the likelihood of a patient's AE after adjustment by the effect of patient characteristic indicators.

Additionally, the effect of HWIs on AEs could vary enormously due to unobservable and heterogeneous characteristics of patients (Berry Jaeker & Tucker, 2012a) or hospitals and hospital units (Van den Heede et al., 2009); known as random effects of HWIs on AEs. However, some studies (Duffield et al., 2011; Evans & Kim, 2006) did not include the random effect of HWIs if they were conducted in a multi-centre context. As occurs when neglecting the effects of patient characteristic indicators, neglecting the random effects of HWIs on AEs

can further undermine the reliability of the adjusted model if they have significant effect on AEs (omitted variable bias effect).

Finally, the selected literature on the association of HWIs with AEs (Duffield et al., 2011; Epstein et al., 2012; Pedroja, 2008; Pedroja et al., 2014; Weissman et al., 2007) did not utilize AEs by using comprehensive and consistent tools. It was observed that the literature failed to capture wide, and sufficient, ranges of AEs and some studies (Tucker et al., 2002, Pines et al., 2009, Epstein et al., 2012) were confined to a particular type of AEs. This can contribute to reason which that some of those studies (Tucker et al., 2002, Pines et al., 2009) have not obtained a significant association between HWIs and AEs. Moreover, the literature failed to use a consistent tool for the identification of AEs, which makes comparison of results among the studies difficult. In contrast, this thesis employs CHADx as a comprehensive and consistent tool for utilization and categorization of AEs based on a variety of prevalent hospital-acquired complications.

It can be observed from this literature review that there are limitations associated with methodologies developed to help understand AE's and their possible links with workload. Firstly, there were only two hospital context studies (Evans & Kim, 2006; Weissman et al., 2007), which examined the association of patient exposure to HWIs with the likelihood of a patients' AE. However, both studies have notable drawbacks. Weissman et al. (2007) examined the association of patient exposure to HWIs with the likelihood of a patient's AE per day. As stated previously, identification of AEs per day is involved with inaccuracy on determining the exact day of occurrences of AEs during the patient's LOS. Therefore, these inaccuracies undermine the proper use of any temporal model of HWIs with AEs, for example a model based on a daily basis. On the other hand, this thesis measures AEs as obtained from the entire patient's LOS.

Secondly, Evans and Kim (2006) examined the association of HWIs (only throughput dimension) with the likelihood of a patient's FTR (death following a hospital-acquired complication); whereas this thesis employs CHADx to capture a wide range of prospective AEs from hospital acquired complications[39] (thus not confined to FTR). Moreover, the studies

[39] The details information regarding the utilization of CHADx to capture AEs from hospital-acquired complications has been provided in Chapter 3, Section 3.4: Identification of AEs from CHADx.

by Weissman et al. (2007) and Evans and Kim (2006) have both employed unadjusted models, which could make the suggested associations overestimated and misleading.

It is notable that CHADx provides a tool for identification of hospital-acquired complications; however, this thesis makes a novel amendment to CHADx to utilize it for identification of AEs from hospital-acquired complications. To the knowledge of the researcher, there is no study that has utilized CHADx for identification of AEs, nor has any previous study has examined the association of HWIs with AEs using the CHADx.

2.5 Conclusion

The literature that has explored the association between HWIs and AEs has been conducted within hospitals and their departments, employing different research designs and different HWIs within different dimensions. It is notable that this literature review was confined to hospital-based literature that employed HWIs from hospital episode datasets. Medication errors and hospital-acquired complications were further included in this review since they were shown to be a significantly associated with the occurrences of AEs. In contrast to HWIs, studies in this review were not confined to those that captured the employed measurements of patient adverse outcomes (medication errors, hospital-acquired complications, AEs) from a hospital episode dataset. This further broadened the numbers of studies reviewed and consequently strengthened the conclusions on the effect of HWIs on the measurements of patient adverse outcomes.

The principal drawback with the literature was attributed to the design of the studies with regard to the absence of comprehensive suites of HWIs. This thesis addresses this limitation by employing fully adjusted and validated models of HWIs with AEs. In addition, the studies in this review revealed significant inconsistency in the measurement of AEs. Notably, there was no consistent tool in the literature to identify AEs from a hospital episode dataset. Considering the merits for conducting this research based on indicators drawn from a hospital episode dataset (refer to Chapter 1, Section 1.5: Hospital Workload Indicators - HWIs), this thesis utilizes CHADx as a consistent tool to identify a wide range of prospective AEs from hospital-acquired complications obtained from a hospital episode dataset.

Furthermore, to the knowledge of the researcher, there is no composite index of patient exposure to HWIs. A composite index would suggest a set of HWIs that are associated with

increased likelihood of a patient's AE based on a prediction model. In contrast, this thesis develops an accurate composite index of HWIs based on indicators drawn from hospital episode datasets. Consequently, this index can provide an effective tool for any future study for the prediction of AEs. The following chapter will introduce the conceptual framework of the thesis and discuss the implementation and validation of the adjusted models by using a sample episode dataset.

Chapter 3: Study Design and Methodology

3.1 Introduction

One of the objectives of this thesis was to develop an accurate and reliable adjusted model of HWIs with AEs; this chapter outlines and describes the methodology and rationale for the implementation of an adjusted model in this thesis. As described in earlier chapters, hospital workload may interact with AEs. Different measures of hospital workload such as peak and median of daily values of HWIs during the patient's LOS and HWIs on the admission date can be used. Based on these measures, various analyses have been conducted to examine the association of HWIs with AEs. For each analysis, a reliable and accurate adjusted model should be constructed. This chapter explains how the adjusted model of HWIs with AEs is conceptualized, developed (data collection and the ethical considerations) and then evaluated and validated.

3.2 Conceptual Framework

It is an essential task for healthcare authorities to meet the complex needs of patients and healthcare service providers by linking the hospital work environment to patient outcomes (O'Brien-Pallas et al., 2004). This can be shown in a conceptual framework, which allows the evaluation of the efficiency of healthcare service delivery by measuring patient outcomes. A conceptual model should link both hospital and patient characteristic indicators, through the pathway of hospital interventions, with patient outcomes (O'Brien-Pallas et al., 2004; Tourangeau et al., 2007; Tvedt, Sjetne, Helgeland, & Bukholm, 2012).

There are two seminal studies (Donabedian, 2002; O'Brien-Pallas et al., 2004) in the literature, which proposed a conceptual framework for measuring the efficiency of healthcare service delivery by measuring the patient outcomes. Donabedian (1988) suggested that patient outcomes are affected by the structure and process of care in hospital environments. The structure was made up of all factors that impact on the context of the healthcare. This included a variety of hospital characteristic indicators, such as the level of employed technology and types of facilities or equipment, along with organizational factors such as staff training methods (Donabedian, 2002). The process of care consisted of all staff interventions that occurred in order to provide healthcare services (Donabedian, 2002). Patient outcomes included a variety of patient adverse outcomes such as AEs, mortality, readmission rates, LOS, and cost (Donabedian, 2002).

Furthermore, O'Brien-Pallas et al. (2004) proposed a Patient Care Delivery Model (PCDM) consisting of three components including inputs, throughput and outputs. The PCDM was proposed to obtain the effect of input on output as adjusted by the effect of throughput. Input consisted of the patient characteristics (demographic information), the nurse characteristics (education level, demographic information) and the hospital characteristics (workload, bed size) along with system behaviours (such as nurse staffing). Throughput was conceptualized by staff intervention in the context of the hospital environment. Throughput is affected by the input and then impacts the output (patient outcomes) (O'Brien-Pallas et al., 2004). Notably, in the PCDM of O'Brien-Pallas et al. (2004), each hospital was characterized by a workload indicator that represented the overall intensity of the workload in the hospital; this workload indicator was employed as an input in the PCDM. The output of the proposed PCDM included patient outcomes (such as LOS, medical consequences, and mortality), as well as nurse (burnout, job dissatisfaction) and system outcomes (hospital quality of patient care, hospital quality of nursing care).

To construct the adjusted model of HWIs with AEs according to the aim of this thesis and its objectives, this study proposes a new conceptual model (Figure 3.1). The proposed model has similarities to the two conceptual models (Donabedian, 2002; O'Brien-Pallas et al., 2004) previously described in this chapter which denote the relationship between patient characteristic indicators (input) through the pathway of hospital interventions (throughput or process) linked to patient outcomes (adverse outcomes). Similar to Donabedian's (1988) model and the PCDM of O'Brien-Pallas et al. (2004), the proposed model in this thesis consists of three main components including input, process and output.

The input to the proposed conceptual model has included patient general characteristics in addition to their episode characteristics and comorbid conditions. The inputs are similar to the inputs of the PCDM of O'Brien-Pallas et al. (2004), and the structure component of Donabedian's (1988) model, which both have components of patient characteristics.

The process in the thesis' conceptual model includes patient exposure to HWIs. To represent the exposure to HWIs, a comprehensive suite of HWIs were included from Weissman et al. (2007) in four broad dimensions. These included volume, throughput, patient complexity and nurse staffing and workload. These dimensions were discussed in detail in Chapter 2. It

should be noted that patients' admissions and discharges (throughput dimension of HWIs) are staff interventions that provide healthcare service delivery to the patients. Therefore, they can be considered within the process of Donabedian's (1988) model. The patients' admissions and discharges further contribute to the hospital volume and hospital patient complexity. Likewise, the concept of patient exposure to HWIs is dependent on patient admission time (input), patient LOS (output), and the overall intensity of hospital workload (input). Therefore, it can be further described by throughput as an indicator that is affected by both input and output of the system (O'Brien-Pallas et al., 2004). It should be noted that the concept of patient exposure to HWIs is different from hospital workload that was used as input in the PCDM of O'Brien-Pallas et al. (2004). The employed hospital workload in O'Brien-Pallas et al. (2004) is a measurement of overall intensity of the workload at the hospital (a hospital demographic characteristic indicator) and should be considered as an input to any conceptual model[40].

The patient outcome was further characterized by the occurrences of AEs. The utilization of AEs in the proposed model is similar to both conceptual models suggested by Donabedian (1988) and O'Brien-Pallas et al. (2004) as they both have a measurement of the quality of patient care (AEs) for the output of their models. The proposed conceptual model of this thesis, which has associated HWIs with AEs, is shown in Figure 3.1.

[40] This workload indicator is not included in the proposed conceptual model of this thesis since this study is a single centre study.

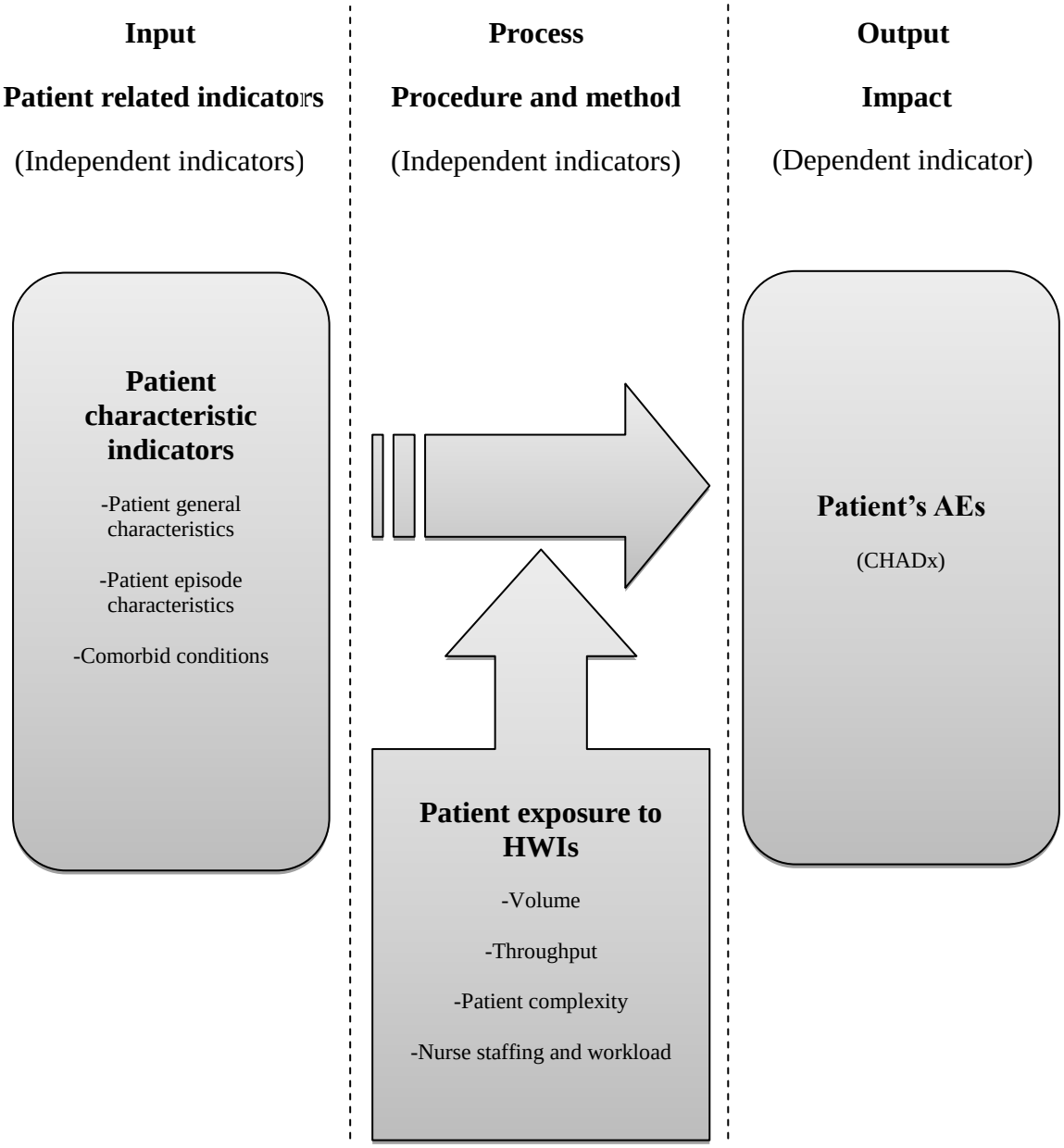


Figure 3.1. Proposed conceptual model of this thesis: 1- Patient Characteristic Indicators (Input) 2- Patient Exposure to HWIs (Process) 3- Patient's AEs (Output).

3.3 Measures

The employed measures for input, process, and outcome indicators and the rationale behind including them in the proposed conceptual model were as follows:

3.3.1 Input (patient characteristic indicators)

Based on the proposed conceptual model (Figure 3.1), independent input indicators related to patient characteristics on or during the hospitalisation were divided into three main categories, including:

1- Patient general characteristics
2- Patient episode characteristics
3- Comorbid conditions

3.3.1.1 Patient general characteristics

The patient general characteristic indicators include indicators that are related to the patient demographic or the type of hospitalisation. Older patients have been associated with an increased likelihood of patient adverse outcomes such as AEs (Bohensky et al., 2013; Miyata et al., 2011)[41] and in-hospital mortality (Person et al., 2004; Sprivulis, Da Silva, Jacobs, Frazer, & Jelinek, 2006). It should be noted that AEs are significantly associated with increased likelihood of in-hospital mortality (Kim et al., 2013; Kim et al., 2012); therefore, the association of the older patient with an increased likelihood of in-hospital mortality could be due to increased likelihood of AEs.

In addition, different types of admissions have varying effects on the likelihood of patient adverse outcomes. For example, it has been suggested that a patient with an emergency type admission (versus elective admission) is associated with increased likelihood of an AE (Miyata et al., 2011), and in-hospital mortality (Kuntz et al., 2014). Following the strong effect of age and admission type on AEs, neglect of their effects result in inaccurate estimations of the association between HWIs and AEs in adjusted models. Therefore, according to the above associations in the literature, the following indicators were employed within the proposed conceptual model to represent patient general characteristic indicators:

- Age
- Sex
- Admission type

Age was employed in this thesis as a continuous variable; sex was either female or male. Admission type was a categorical variable including six values:

[41] It is notable that Bohensky et al. (2013) considered AEs as the adverse outcomes following an elective knee arthroscopy. Miyata et al. (2011) considered AEs as complications acquired following cardiovascular surgery.

- Casualty and Accident and Emergency (A&E)
- Change from psychiatric or psychogeriatric units
- Referral from local medical officer (LMO)
- Qualified and unqualified new-born
- Transfer from other acute hospital external care rehabilitation and geriatric centres
- Waiting list.

3.3.1.2 Patient episode characteristics

Patient episode characteristics indicators, as the name suggests, describe the characteristics of the patient's episode of care. As described earlier (refer to Chapter 2: Section 2.2.2: HWIs), a higher patient's individual complexity (represented by Weighted Inlier Equivalent Separation - WIES value[42]) has been associated with an increased likelihood of a patient's AE (Hauck et al., 2012). Similarly, the number of procedures a patient has undergone during the treatment has been associated with an increased likelihood of a patient's AE (Hauck et al., 2012). Moreover, some studies have suggested a significant effect of the date of admission, such as weekend admissions (versus weekday admissions), on the increased likelihood of a patient's hospital-acquired complication and AEs (Attenello et al., 2015) and in-hospital mortality (Barba et al., 2006; Bell & Redelmeier, 2001; H.-J. Kim et al., 2015; Kuntz et al., 2011; Schilling et al., 2010). Emerging from the above associations obtained from the literature, the following patient episode characteristics indicators were employed in the proposed conceptual model:

- Adjacent DRG cost weight (DRGs without the effect of comorbid conditions and complications)
- Number of procedures
- Date of admission
- Discharge status

DRG cost weight is a measurement of the severity of illness, as a patient with a higher DRG cost weight requires more hospital resources for treatment. In this thesis, the adjacent DRGs were employed instead of DRGs because the adjacent DRGs do not take into account the

[42] According to Department of Health - State of Victoria (2014d, p. 45), "a cost-weighted separation is called a WIES and is calculated using different cost weights (weighted) for different types of stay (inlier equivalent separation) within each DRG".

effect of complications (prospective AEs); these complications are already employed as the output of the proposed conceptual model (Figure 3.1).

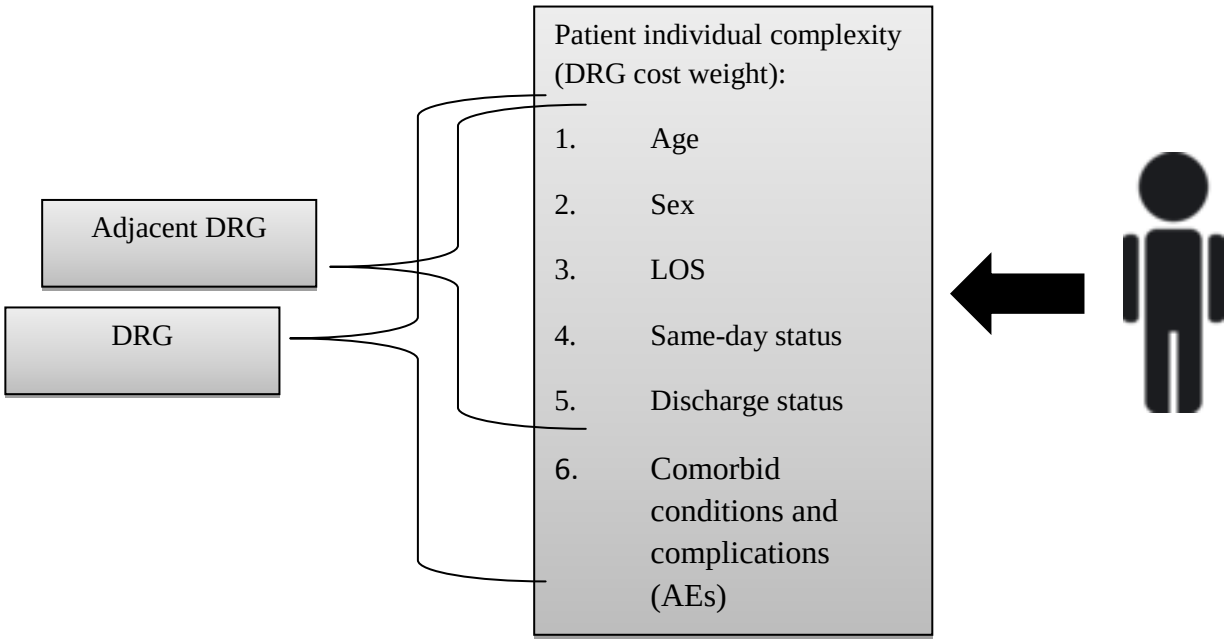


Figure 3.2 Individual Patient Complexity (Department of Health - State of Western Australia, 2012).

An adjacent DRG code was obtained from the first three characters of a DRG code. To obtain the adjacent DRG cost weight, the average of DRG cost weights of all DRGs in the corresponding adjacent DRG was calculated. The number of procedures was obtained based on the number of procedures the patient underwent during hospitalisation. Date of admission was employed in this thesis' conceptual model as a categorical variable representing the day of the week on which the patient was admitted. This included three binary variables:

- Weekends
- The day before and after weekends
- Weekdays

Discharge status was a categorical variable including nine values:

- Change to psychiatric or psychogeriatric units
- Change to designated rehab program/unit levels
- Change to Nursing Home Transition (NHT)
- Death

- Discharge to home without support
- Left against medical advice
- Transfer to nursing home
- Transfer to other acute hospitals/external care facilitates/rehabilitation and geriatric centres
- Other formal separation (all separations except above)

3.3.1.3 Comorbid conditions

Patient individual complexity or severity of illness (as utilized by the patient's DRG – Figure 3.2) was a factor considered in this thesis. Patient complexity is a significant factor among the patient characteristic indicators that its higher values increase the likelihood of a patient's AE (Hauck et al., 2012). The presence of comorbid conditions is one of the factors used to determine the patient individual complexity (Figure 3.2). Comorbid conditions refer to diseases that co-exist with each other at the time of admission, excluding the main underlying disease, which is referred to as the primary diagnosis (Jakovljević & Ostojić, 2013). There is a significant association between the presence of comorbid conditions with an increased likelihood of a patient's AE (Bohensky et al., 2013). It should be noted that since this thesis employed adjacent DRGs (instead of DRGs), the effect of comorbid conditions did not contribute to the determination of patient individual complexity (Figure 3.2). Hence, in addition to patient individual complexity (represented by adjacent DRG), comorbid conditions were also employed as the part of the proposed conceptual model (Figure 3.1).

Several comorbidity indexes have been developed to help practitioners identify the risk factors associated with comorbid conditions. Charlson et al. (1987) and Elixhauser, Steiner, Harris, and Coffey (1998) developed two major comorbidity indexes that have been employed extensively in the literature (Bohensky et al., 2013; Duffield et al., 2011; Schilling et al., 2010). This thesis employed the Charlson Comorbidity Index, as it is the most commonly used index in the literature (Sharabiani, Aylin, & Bottle, 2012). Moreover, it has a simpler structure (fewer comorbid conditions) than the Elixhauser Index, making the employed adjusted models in this thesis less complex. The Charlson Comorbidity Index assigns a severity score to each comorbid condition. The severity score is based on the prediction of ten-year mortality rates within an employed episode dataset obtained in 1984. The Charlson Comorbidity Index includes 30 comorbid conditions within 10 major

categories. These categories include diseases related to myocardial, vascular, pulmonary, neurologic, endocrine, renal, liver, gastrointestinal, cancer, and other miscellaneous conditions (Charlson et al., 1987)[43].

After consideration of the suitability of using severity scores as published in the original implementation by Charlson et al. (1987) it was decided not to employ the original scores in this thesis; this was due to the probability that these scores were unlikely to elicit an accurate complexity measurement when applied to different patients within different time periods (2001 versus 1987) and location (Australian versus American context). Therefore, comorbid conditions in this thesis were proposed as categorized and binary variables for each Charlson comorbid condition. Another reason for employing the comorbid conditions as categorized variables was that, in contrast to a scoring scheme that provides a crude score, the categorized variables identify the exact comorbid condition as related to each Charlson comorbid condition. Therefore, the effect of each comorbid condition on AEs can separately be examined and analysed.

Furthermore, with the introduction and implementation of the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10) codes[44], some adaptations of the Charlson Ccomorbidity Index have employed ICD-10 codes for identification of the comorbid conditions (Deyo, Cherkin, & Ciol, 1992; Halfon et al., 2002; Quan et al., 2005). The employed dataset in this thesis, used the Australian Refined Diagnosis Related Group (AR-DRG)[45] version 4.2. AR-DRG version 4.2[46] has been developed based on ICD-10-Australian Modification (ICD-10-AM)[47] codes. For this reason, this thesis employed the adaptation developed by Quan et al. (2005) as this implementation was one of the most recent works adapting the Charlson Comorbidity Index to be used within the ICD-10 codes. The implementation includes 17 major comorbid conditions using separate binary variables as follows:

[43] For detailed information regarding these conditions and their relative severity scores, readers are referred to the study by Charlson et al. (1987) Table 1 and Table 2, respectively.
[44] According to WHO (1992, p. 3), "ICD-10 as whole is designed to be a central (core) classification for a family of diseases and health related classification".
[45] AR-DRG provides a clinically meaningful way of associating the number and type of patient (casemix) to the required hospital resources for the treatment (AIHW, 2013).
[46] Detailed information regarding AR-DRG version 4.2 including codes and the types of DRGs has been provided in Appendix D.
[47] ICD-10-AM includes extensions of the World Health Organization (WHO)'s ICD-10 codes and some specific Australian diseases codes that are used within Australian hospitals contexts (Roberts et al., 1998).

- AIDS/HIV
- Cerebrovascular disease
- Chronic pulmonary disease
- Congestive heart failure
- Dementia
- Diabetes with chronic complication
- Diabetes without chronic complication
- Hemiplegia or paraplegia
- Malignancies including lymphoma and leukaemia except malignant neoplasm of skin
- Metastatic solid tumour
- Mild liver disease
- Moderate or severe liver disease
- Myocardial infarction
- Peptic ulcer disease
- Peripheral vascular disease
- Renal disease
- Rheumatic disease

Detailed information on the implementation of the Charlson Comorbidity Index by Quan et al. (2005), including the related ICD-10 codes for each comorbid condition, has been provided in Appendix B.

3.3.2 Process (HWIs)

Based on the proposed conceptual model (Figure 3.1), HWIs as independent indicators (as process) were adapted from the four broad dimensions described by Weissman et al. (2007) study:

1. Volume
2. Throughput
3. Patient complexity
4. Nurse staffing and workload

3.3.2.1 Volume

According to Weissman et al. (2007), volume indicators were utilized to denote hospital bed occupancy. Bed occupancy has been considered in many studies as the percentage of occupied

beds out of the whole number of hospital beds available (Pines et al., 2009; Weissman et al., 2007; Zhou et al., 2012). Similarly, this thesis obtained daily 'number of patients' from the hospital episode dataset as a measurement of hospital volume. This indicator is equivalent to bed occupancy, since it needs to be divided by the number of hospital beds which was assumed to be a fixed value during the study period.

3.3.2.2 Throughput

The number of admissions and discharges comprised the throughput dimension of HWIs (Weissman et al., 2007). This thesis also sought to separately examine the association of different types of admissions, such as medical and surgical admissions, with the likelihood of patients' AEs. This is due to the fact that exposure to different types of admissions can have varying effects on the likelihood of a patient adverse outcome. Berry Jaeker and Tucker (2012a) demonstrated this difference on the LOS[48]. Likewise, it is possible for different admission types to have different associations with AEs, since the occurrences of AEs are also associated with a higher patient's LOS (Jackson et al., 2011; Jackson et al., 2011). In other words, the different effects of numbers of medical and surgical admissions on a patient's LOS could be due to different effects on the likelihood of a patient's AE.

The predictability of admission is another aspect of throughput indicators that was incorporated into this thesis. The predictability of admissions was utilized by the percentage of emergency admissions for each day a patient is in the hospital. It is known that hospital staff cannot foresee emergency admissions. Therefore, exposure to higher numbers of emergency admissions can be associated with an increased likelihood of patient adverse outcomes. Confirming this view, it was demonstrated that exposure to more predictable admissions (scheduled versus emergency admissions) resulted in a lower patient's LOS (Berry Jaeker & Tucker, 2012b) and lower likelihood of a patient's AE (Duffield et al., 2011). Following the above discussions, four throughput indicators were employed in this thesis:

- Number of medical admissions
- Number of surgical admissions
- Number of discharges
- Percentage of emergency admissions

[48] This effect is known as spill-over effect (Berry Jaeker & Tucker, 2012b). It is notable that it was not intended to separate the 'number of patients' for examination of the spill-over effect as it was intended to imply the hospital bed occupancy.

The numbers of medical and surgical admissions were obtained from patients' DRG types. Each DRG can be classified as either medical, surgical or other type DRGs (AIHW, 2014a). Patients within surgical DRGs were considered to have surgical admissions while medical DRG patients or other type DRGs, which were not involved with surgery were considered to have medical admissions. Appendix D provides the list of AR-DRG codes and their corresponding classifications to either medical or surgical patents for identification of number of medical and surgical admissions[49].

3.3.2.3 Patient complexity

In this thesis, the patient complexity dimension of HWIs was obtained from patients' DRG cost weights. DRG cost weight is an effective measure for obtaining patient complexity as it represents an estimated cost associated for the treatment of patients (Weissman et al., 2007). Patients with clinically similar resource-intensive burden are assigned identical DRGs and DRG cost weights. The DRG cost weights are obtained from national hospital episode datasets. In this way, the average cost of all DRGs is set to a reference value of one. Thus, each DRG cost weight indicates how much patients within the DRG contributed to the expenditure of the hospitals in comparison to whole patients within all DRGs (IHPA, 2004).

The patient complexity in this thesis' conceptual model is conceptualized by two components. One is individual patient complexity (input to the conceptual model) and the other one is the patient complexity dimension of HWIs (process to the conceptual model) (Figure 3.1). It should be noted that while this thesis' conceptual model employed the adjacent DRGs for measuring individual patient complexity, the DRG cost weights (average of hospital patient DRG cost weights) were used to obtain the patient complexity dimension of HWIs. Patient complexity dimension of HWIs needs to capture the full aspect of hospital patients' complexity (Figure 3.2) for measuring the exposure of the patient to hospital patients' complexity.

[49] As a result of the employed episode dataset in this thesis, the AR-DRG version 4.2 (Appendix D) was used to differentiate different types of patients. This version of AR-DRG contains 662 DRGs (374 medical DRGs, 280 surgical DRGs and 34 other types) (IHPA, 2004). The minor other type DRG groups were excluded from the analyses.

3.3.2.4 Nurse staffing and workload (a proxy measure)

The nurse staffing and workload indicator is one of the four dimensions of HWIs adopted from Weissman et al. (2007). As hospital episode datasets do not contain any explicit information regarding nurse-staffing indicators (Department of Health - State of Victoria, 2012), this thesis employed nursing DRG cost weight as a proxy measurement to denote nurse staffing and workload dimension of HWIs.

According to IHPA (2004, para. 1), nursing DRG cost weights include all costs associated with nursing care in general ward areas. The nursing DRG cost weight is calculated in the same way as DRG cost weights. However, the difference is that for DRG cost weight, all costs related to hospital treatment such as medical clinical services, nursing clinical services, pathology, imaging, allied health, operating room and emergency departments are considered. In contrast, for nursing DRG cost weights, only the cost component related to nursing clinical services is considered (IHPA, 2004). Like the DRG cost weight, the nursing DRG cost weight is extractable from hospital episode datasets through the identification of the patient's DRG.

Exposure to patients with higher nursing DRG cost weights is associated with patients having a higher need for nursing clinical services (IHPA, 2004). It is expected that higher need for nursing clinical service results in higher need for nurse staffing and workload. Therefore, in this thesis, the nursing DRG cost weight was employed as a proxy measurement for the nurse staffing and workload dimension of HWIs. To the knowledge of the researcher, this indicator has not been used in previous literature; therefore, the implications of the effect of this indicator on AEs are innovative.

3.3.2.5 Patient exposure to HWIs

Having provided a description of the HWIs as the process within the proposed conceptual model (Figure 3.1), this section explains the concept of patient exposure to HWIs. As stated in the introductory chapter (Section 1.6: Aims and Objectives), this thesis aims to examine the association of HWIs with the likelihood of a patient's AE when both are derived from hospital episode datasets. Different patients are exposed to different hospital workload intensities, based on their LOS and time of admission. In order to determine patient exposure to HWIs, HWIs were calculated on a daily basis using daily HWIs (DHWIs) during the patient's LOS. Based on DHWIs, different measurements of HWIs were utilized. These measurements were obtained via statistical functions (such as mean, peak, average and median). These functions

were either applied to DHWIs during the entire LOS or on particular days. Patient exposure to HWIs during the patient's entire LOS, used median and peak values. On the other hand, patient exposure to HWIs on particular days used DHWIs on a specific day such as the first day of the patient's hospitalisation. Employing all of these measurements (peak, median, first day) enables the examination of the association between HWIs and AEs based on the time effect of HWIs. Figures 3.3 and 3.4 clarify these differences.

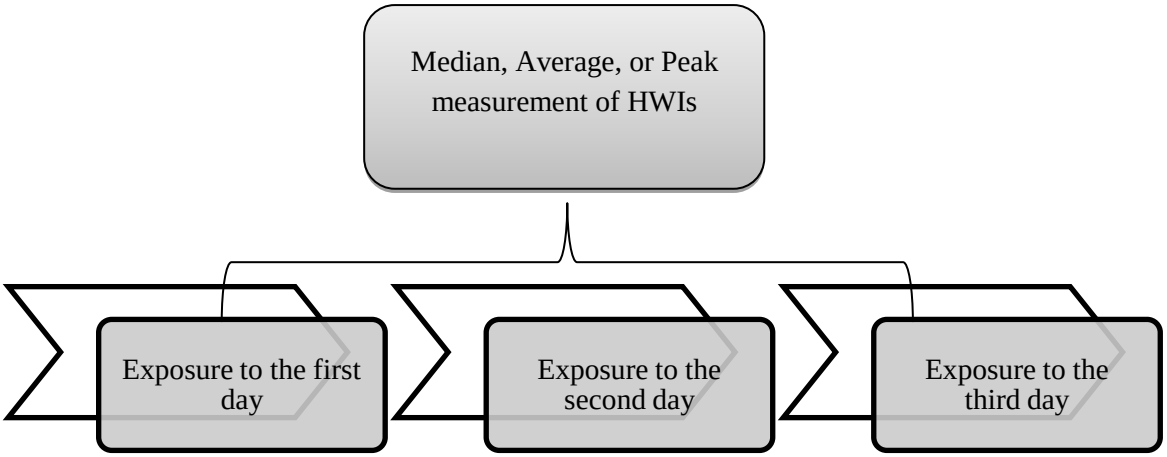


Figure 3.3 Patient Exposure to HWIs During the Patient's Entire LOS.

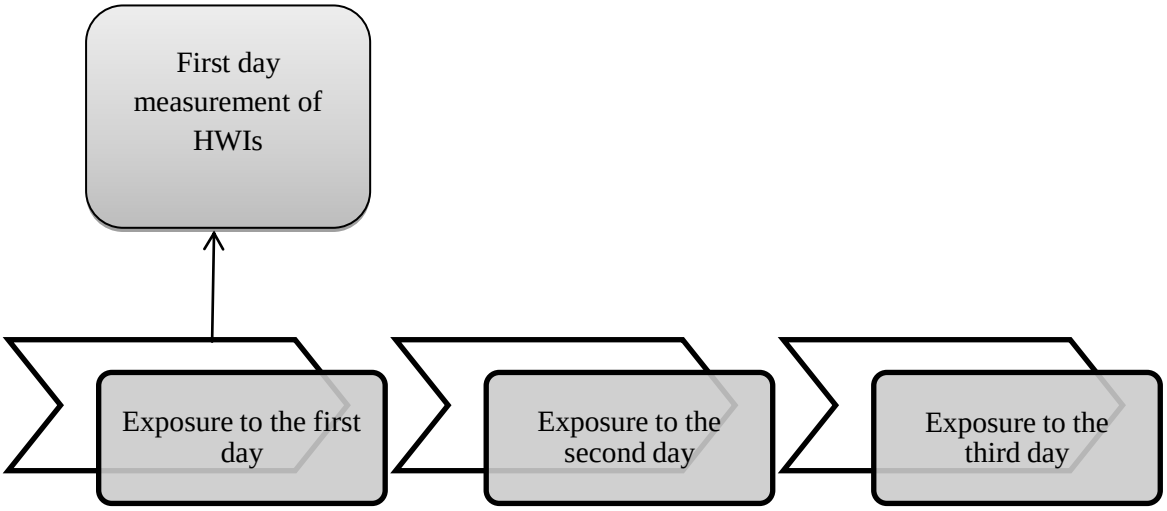


Figure 3.*4* Patient Exposure to HWIs on a Particular Day.

To elaborate on the concept of patient exposure to HWIs, Table 3.1 provides an example including a sample episode dataset containing four medical patients' episodes of care.

Table 3.1

An Example of all Medical Patients Recorded in an Episode Dataset Between 1st March and 5th March.

Patient ID	Admission date	Discharge date	DRG cost weight	Nursing DRG cost weight
1	1st March (12:00 a.m.)	3rd March (12:00 a.m.)	1	1
2	1st March (12:00 a.m.)	3rd March (12:00 a.m.)	1	1
3	2nd March (12:00 a.m.)	5th March (12:00 a.m.)	2	4
4	2nd March (12:00 a.m.)	5th March (12:00 a.m.)	2	4

Based on the above information, there were two medical admissions on the 1st of March and the 2nd of March. There were no admissions on the 3rd - 5th of March. Further there were two daily hospital discharges on the 3rd and 5th of March, and on the other days (1st - 3rd March) there were no discharges. Consequently, there were two patients (bed occupancy rate) on the 1st, 3rd, and 4th March and for 2nd of March, there were four existing patients. The sum of DRG cost weight on the 1st of March was calculated as two; for the 2nd of March it was calculated as six; and for other days (3rd - 4th of March) it was calculated as four. The sum of the nursing DRG cost weight on the 1st of March were calculated as two; for the 2nd of March calculated as ten; and for other days (2nd - 4th of March), they were calculated as eight.

Patient exposure to HWIs, were calculated based on the time of patient's admissions and discharges and the number of existing patients for each day during the patient's LOS. From the above table, it is inferred that a patient with ID = 1 is exposed to two medical admissions on the day of admission. However, the patient is exposed to an average daily number of medical admissions of two (Average of 2, 2), and a peak of two medical admissions (Maximum of 2, 2), during the LOS. Similarly, the patient is exposed to an average[50]of DRG cost weight of one on the admission date, a peak average of DRG cost weights of two (Maximum of 1, 2), and the median average of DRG cost weight 1.5 (Median of 1, 2) during the LOS. Patient exposures to other HWIs were calculated similarly.

[50] It should be noted that, the daily measurement of DRG and nursing DRG cost weights were calculated by average values instead of sum values. This is because the average measurements for DRG and nursing DRG cost weights will have less correlation to the measurement of bed occupancy (number of patients) in the analysis of this thesis.

It should be noted that this thesis constructed separate adjusted models for each measurement (median, peak, and first day). This was necessary to avoid the inter-correlation effects of HWIs, especially for the same indicator when employed by different measurements of HWIs.

3.3.3 Output (AEs)

Since this thesis aims to examine the association of HWIs with AEs, it solely employed AEs as the output of the proposed conceptual model (Figure 3.1) for the measurement of patient outcomes. There are various methods for the identification of AEs outlined in the following section.

3.3.3.1 Different methods for identification of AEs

Several methods for the identification of AEs have been employed in the literature. These methods include spontaneous (voluntary) reporting (Pedroja, 2008; Pedroja et al., 2014; Tibby et al., 2004), chart review (retrospective medical record reviews) (Weissman et al., 2007), patient interviews (Fowler et al., 2008), nurse interviews (Al-Kandari & Thomas, 2009; M. Elliott et al., 2013; Nielsen et al., 2013) or by use of hospital episode datasets (Duffield et al., 2011). There are disadvantages associated with each method. For example, spontaneous reporting requires a considerable number of resources but misses the detection of vast ranges of AEs due to the reluctance of staff to report them (Murff, Patel, Hripcsak, & Bates, 2003). On the other hand, while the chart review method may be more accurate than spontaneous reporting, it is similar to spontaneous reporting in that it is impractical for large-scale studies due to the need for extensive resources (Murff et al., 2003). Likewise, while patient and nurse interview may provide complementary information for identification of AEs (Fowler et al., 2008) it also requires substantial resources and commitment by patients and nursing staff (Murff et al., 2003). Finally, using hospital episode datasets relies on other methods for detection of AEs, such as clinicians' inputs into charting and medical records . Moreover, using a hospital episode dataset relies on interpretations by a coder, which may be subject to the misinterpretations or errors while coding the patients' medical records.

However, while the aforementioned limitations continue to exist, identification of AEs through hospital episode datasets has improved over recent years (Michel, Cheng, & Jackson, 2011). Hospitals use well supported systems for recording patients' medical records with the data even more complete in comparison to the past (Michel et al., 2011). In addition, hospitals use well trained and highly qualified coders for coding patient medical records, which reduces

coder-related errors (Jackson et al., 2009). Identification of AEs through hospital episode datasets is more cost-effective, timely and accessible in comparison to manual methods (spontaneous reporting, chart review, patient interviews) for detection of AEs (Michel et al., 2011; Murff et al., 2003). Hence, hospital episode datasets provide a time and cost effective means for the identification of AEs. Apparently, this advantage is more achievable using a retrospective study investigating the evidence of previous patients medical records on a large scale.

3.3.3.2 Classification of Hospital-acquired Diagnoses (CHADx)

This thesis employed the CHADx (ACSQHC, 2010) to extract and identify potential AEs from hospital-acquired complications using hospital episode datasets. CHADx provides hospitals with a tool to measure their performance and safety indicators through examining the rate of hospital-acquired complications (ACSQHC, 2010).

There are similar tools to CHADx for the identification of hospital-acquired complications from hospital episode datasets. These tools include Patient Safety Indicators (PSIs) (Miller, Elixhauser, Zhan, & Meyer, 2001), Variable Life Adjusted Display (VLAD) (Duckett, Coory, & Sketcher-Baker, 2007), and Potentially Preventable Complications (PPC) system (Hughes et al., 2006). However, in comparison to CHADx, these tools employ a very small range of complications. For example, VLAD's complications have been confined to diagnoses of patients' surgery (Duckett et al., 2007). Moreover, the above tools are based on out-dated ICD-9-CM codes. This thesis employed the fifth and latest version of CHADx, which was developed in 2013 (ACSQHC, 2013); this version of CHADx includes more than 45,000 ICD-10-AM diagnosis codes of hospital-acquired complications within 17 major and 145 minor categories. The major categories are as follow:

- CHADx 1: Post procedural complications
- CHADx 2: Adverse drug events
- CHADx 3: Accidental injuries
- CHADx 4: Specific infections
- CHADx 5: Cardiovascular complications
- CHADx 6: Respiratory complications
- CHADx 7: Gastrointestinal complications
- CHADx 8: Skin conditions

- CHADx 9: Genitourinary complications
- CHADx 10: Hospital-acquired psychiatric states
- CHADx 11: Early pregnancy complications
- CHADx 12: Labour, delivery & postpartum complications
- CHADx 13: Perinatal complications
- CHADx 14: Hematological disorders
- CHADx 15: Metabolic disorders
- CHADx 16: Nervous system complications
- CHADx 17: Other complications

As described earlier (refer to Chapter 2: Section 2.2.1: Adverse outcomes), hospital-acquired complications represent an AE if their occurrences can be attributed to a hospital-related external cause code. The wide range of hospital-acquired complications as described by CHADx makes it a comprehensive tool to extract a wide range of potential AEs. This thesis makes a novel amendment to CHADx to identify AEs from hospital-acquired complications. This amendment is described in the following section (Section 3.4: Identification of AEs from CHADx).

3.3.4 Summary of employed indicators

Table 3.2 shows a summary of employed indicators in this thesis' conceptual model (Figure 3.1). Dependent and independent indicators have been summarized in detail for all three components (input, process, output) of the proposed conceptual model.

Table 3.2

Employed Dependent and Independent Indicators in the Proposed Conceptual Model.

Independent indicators		**Dependent indicator**
Input (patient characteristics indicators)	**Process (HWIs)**	**Output (AEs)**
1-Patient general characteristics (age, sex, admission type)	1- Number of medical admissions	1-Patient's likelihood of an AE (17 CHADx categories)
2-Patient episode characteristics (Adjacent DRG cost weight, number of procedures, date of admission, discharge status)	2-Number of surgical admissions	
3- Comorbidity diseases (Charlson index)	3-Number of discharges	
	4-Percentage of emergency admissions	
	5-Number of patients (bed occupancy)	
	6- Average of patients' DRG cost weights	
	7- Average of paients' nursing DRG cost weights	

3.4 Identification of AEs from CHADx

CHADx identifies a wide range of hospital-acquired complications in 17 major categories. This is identified via compliance with the CHADx business rules for each major category. CHADx business rules include a set of conditions that determine if an ICD-10-AM diagnosis code in the patient's secondary diagnosis, is attributable to a particular CHADx category[51]. As an example, the majority of the CHADx major categories (Except CHADx 13 - perinatal complications) necessitate the existence of an 'onset flag' indicator, to assign a secondary diagnosis to a hospital-acquired complication (ACSQHC, 2013). The onset flag indicator explicitly implies the underlying cause of diagnosis occurred after the time of patient admission or during the hospitalisation (ACSQHC, 2010). Thus, the onset flag indicator would differentiate complications from other types of diseases, such as comorbid conditions, where causes have occurred before the time of admission. However, in this thesis, identification of AEs from CHADx is obtained by a novel algorithm which could dismiss some of business rules of CHADx. This information is provided in detail in this section.

It should be noted that patients' diagnoses include two major types, namely primary and secondary diagnoses. The primary diagnosis indicates the underlying cause of the illness for which the patient has been hospitalised. Other peripheral diagnoses are coded as secondary diagnoses within the patient's episode of care. Both complications (AEs) and comorbid conditions can be extracted from the secondary diagnoses list.

This thesis utilizes CHADx to identify AEs from hospital-acquired complications. This is obtained by complying with two assumptions:

1. The CHADx complications would genuinely represent an AE.
2. The CHADx complications are acquired due to a hospital-related external cause code.

Some CHADx complications (corresponding to categories and subclasses) genuinely represent an AE. This means that these types of complications have been acquired during hospitalisation and are a result of the hospital treatment (the definition of AEs). This can be identified by their corresponding ICD-10 codes; some of these codes are related to complications which genuinely represent an AE. For example, codes in the range of T80-T88.9 are related to specific complications due to a medical or surgical treatment and

[51] Detailed information regarding CHADx categories, business rules and their related ICD-10 codes has been provided in Appendix C.

genuinely imply an AE (Jackson et al., 2006). In addition, the end of chapter codes denote the specific injuries at the end of each chapter of ICD-10-AM classification representing AEs (Jackson et al., 2006). CHADx 1 (post-procedural complications) consists of all end of chapter codes and codes in the range of T80-T88.9. Therefore, all diagnoses in CHADx 1 genuinely represent an AE.

Furthermore, according to the Australian Coding Standards (ACS)[52] (Australian Consortium for Classification Development (ACCD, 2014)) each diagnosis should be accompanied by an extra code representing the external cause of that diagnosis. By definition, the external cause codes in the range Y40-Y84.9 imply the cause of diagnosis was based on medical or surgical treatment (Jackson et al., 2006). In addition, the external cause code of Y95 denotes a hospital-acquired disease (nosocomial condition) due to the underlying hospital treatment (Jackson et al., 2006). The external cause code of Y92.22 denotes the place where an injury occurred was within a health facility (Jackson et al., 2006). Therefore, for the CHADx classes which do not genuinely represent an AE (all CHADx categories except CHADx 1)[53], the employed approach in this thesis considered them an AE if they were immediately followed by any hospital-related external cause code. These hospital-related external cause codes either stipulate an AE as the result of hospital medical or surgical treatments (Y40-Y84.9) or imply that the hospital environment was the cause of the occurrence of an AE (Y95, Y92.22). It should be noted, based on the above assumption, all subclasses in CHADx 2 (adverse drug events) would also genuinely imply an AE since the business rules in CHADx 2 stipulate that the CHADx 2 diagnoses should be followed by a hospital-related external cause code. Overall, all aforementioned external cause codes (Y40-Y84.9, Y95, Y92.22) were applied as a prerequisite condition to all CHADx categories (except CHADx 1 subclasses) to identify AEs from CHADx diagnoses based on 17 major categories[54].

The possibility exists that there could be some diagnosis codes which were not matched with any CHADx categories' diagnoses when they were immediately followed by a hospital-related external cause code. The employed approach in this thesis considered these type of AEs as an extension of the CHADx 17 category (other complications) AEs.

[52] ACS is employed as a supplementary tool to assist the clinical coders to satisfy coding conventions within ICD-10-AM classification systems (ACCD, 2014).
[53] Detailed information regarding the aforementioned CHADx categories' ICD-10 codes has been provided in Appendix C.
[54] The details of the CHADx categories' diagnoses have been provided in Appendix C.

It should be noted that the two aforescribed assumptions made in this thesis to consider a hospital-acquired complication as an AE would dismiss the necessity of existence of the onset flag indicator on the diagnosis (Jackson et al., 2006). Therefore, the aforementioned method suggested for identification of AEs from CHADx is completely applicable on the employed dataset in this thesis[55].

It should be taken into account that, other types of patient adverse outcomes such as medication errors or death, are not considered as an AE. As stated previously, only medication errors which cause an injury can denote an AE. Furthermore, only the deaths (and FTRs[56]) acquired due to the hospital-related external cause code can be considered as an AE. As this thesis seeks to identify AEs from hospital acquired complications (CHADx) due to a hospital-related external cause code, the detection of AEs resulting from medication errors or death are not explicitly addressed. However, with regard to medication errors, this thesis identifies the CHADx 2 AEs (Adverse Drug Events) mainly due to drug-related medication errors. Therefore, this thesis identifies the association between HWIs and drug – related medication errors. This is achieved by conducting a subgroup analysis of AEs, which is further discussed in the following section (3.8.4).

The method utilized in this thesis differentiates comorbid conditions from AEs or hospital-acquired complications. As the employed episode dataset in this thesis did not include an onset flag indicator, this thesis utilizes an approach to differentiate comorbid conditions from hospital-acquired complications and AEs. Firstly, a diagnosis was considered a comorbid condition if the diagnosis was not matched with any AEs proposed by the above approach. That is where the condition was not immediately followed by a hospital-related external cause code. Moreover, it should not represent a complication that genuinely represents an AE (CHADx 1). Secondly, a diagnosis was considered a comorbid condition if it did not genuinely represent a hospital-acquired complication. It should be noted that some

[55] It should be noted that some CHADx subclasses such as 3.1 (falls with fractured femur), 3.2 (falls with intracranial injury), 3.3 (all other falls), 4.1 (sepsis), 4.3 (methicillin resistant agent), 4.4 (other drug resistant infections), 4.5 (other infectious agents), and 8.1 (pressure ulcers) could imply an AE (Utz et al., 2012). These subclasses need to be a hospital-acquired complication identified by an onset flag indicator to reprent an AE. Since there was no onset flag indicator in this thesis' dataset, the aforementioned classes were considered as an AE if they were only followed by a hospital-related external cause code.

[56] FTRs can be identified from hospital episode data using those episodes which have death as their discharge status that follows some specific complications (Department of Health - State of Queensland. 2009).

complications in CHADx genuinely represent a hospital-acquired complication regardless of the presence of an onset flag indicator. This includes all diagnoses in CHADx subclasses 12.1 (foetal heart anomalies), 12.4 (unsuccessful interventions during labour), 12.6 (first degree and unspecified perineal tear during delivery), 12.7 (second degree and unspecified perineal tear during delivery), 12.8 (third and fourth degree perineal tear during delivery) and CHADx 13-all subclasses (perinatal complications)[57] (ACSQHC, 2013). Simply put, to consider a diagnosis as a comorbid condition, it should neither represent an AE nor a hospital-acquired complication.

One limitation of the above method of determining comorbid conditions is that, in the absence of an onset flag indicator on the diagnoses, the proposed approach for the differentiation of comorbid conditions from AEs and hospital-acquired complications can result in an inaccurate estimation of the rate of comorbid conditions. This is because a hospital-acquired complication (a complication which is not an AE or a genuine hospital-acquired complication) could be considered a comorbid condition due to the absence of the onset flag indicator in this thesis' dataset. Moreover, a comorbid condition could be placed after a hospital-related external cause code due to the hospital coder's error and misinterpretation.

To extract the rates of AEs, Carroll, McLean, and Walsh (2003) also used hospital-related external cause codes for hospital-acquired complications. However, in comparison to this study, they used less hospital-related external cause codes (only Y40-Y84.9 and Y92.22). To the knowledge of the researcher, the utilization of CHADx to capture AEs from hospital-acquired complications is an innovative method in the literature. Figure 3.5 shows a summary of the proposed approach for the identification of AEs from CHADx's complications and differentiation of comorbid conditions from potential hospital-acquired complications and AEs.

[57] Detailed information regarding the aforementioned CHADx categories' ICD-10 codes has been provided in Appendix C.

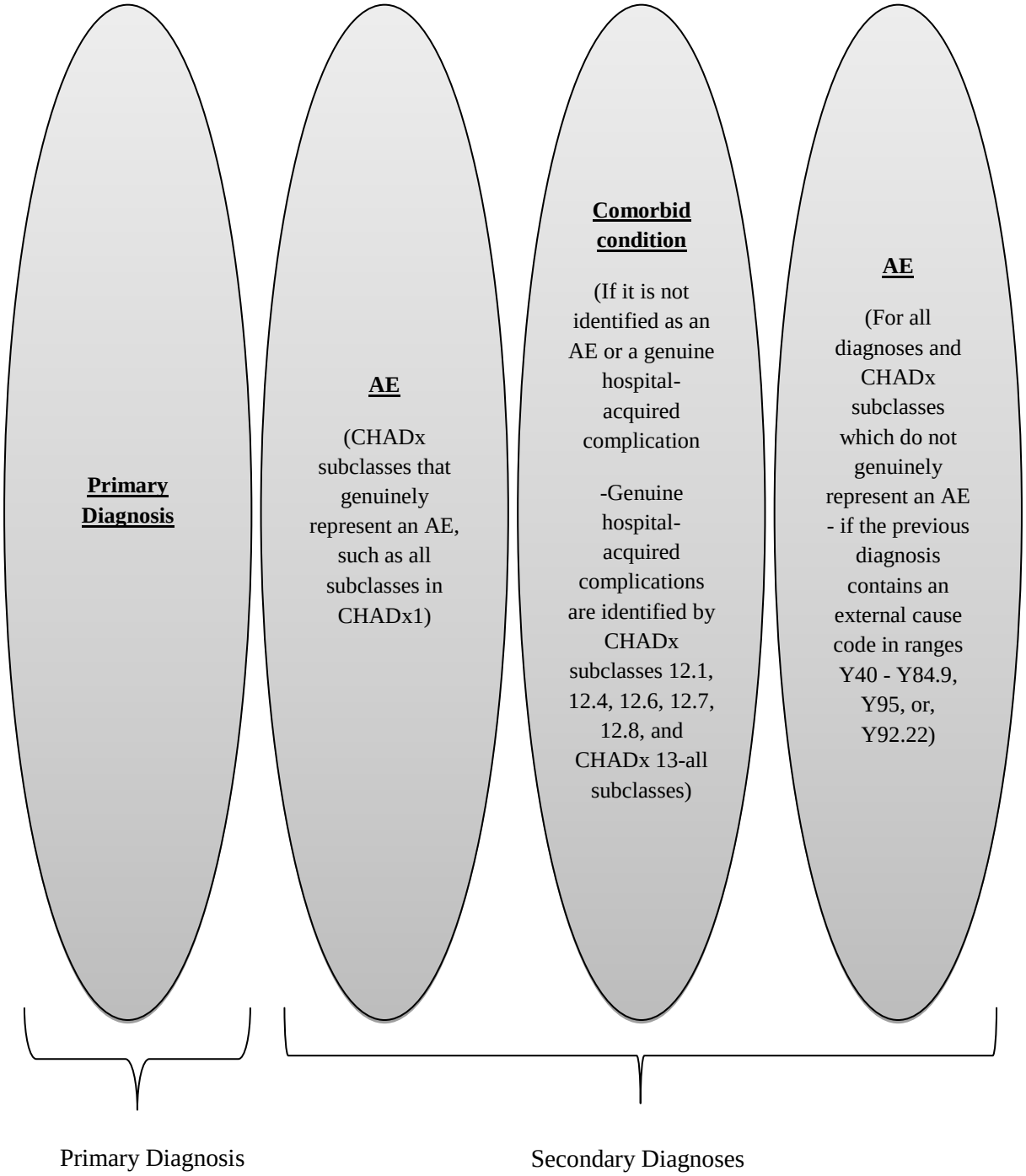


Figure 3.5 Differentiation of Comorbid Conditions from AEs.

It should be noted there are many advantages associated with employing CHADx in this thesis. Firstly, it provides a comprehensive list of complications through the use of ICD-10-AM codes that can be used to identify AEs using hospital episode datasets. Secondly, it leads to categorization of prospective AEs based on different types of complications (CHADx categories). This enables this thesis to conduct further analyses such as the association of

HWIs with a particular type of AE[58]. Thirdly, usage of CHADx in this thesis enables similar and prospective studies to compare their results with this study due to the consistency of the CHADx. Lastly, CHADx was developed and applied in an Australian context.

3.5 Evaluation of the Proposed Conceptual Model

For evaluation of the proposed conceptual model (Figure 3.1), the episode dataset, including all cohorts of patients (n=1,000), was employed to construct pilot adjusted models. For this purpose, a binary logistic regression model was employed using the Statistical Package for the Social Sciences (SPSS) version 22.0. This model included all elements of the proposed conceptual model including input and process indicators (Table 3.2). HWIs were further utilized by median, peak and first day values. Therefore, three separate regression models were constructed. In the model employing median values, the omnibus test revealed significant reliability ($\chi 2$ (1, 42) = 451.666, $p < .001$) showing that it fitted well with the employed episode dataset. The model classified 80.4% of the total cases. Using the model employing peak measurement of HWIs, the omnibus test revealed significant reliability of the constructed model ($\chi 2$ (1, 42) = 486.106, $p < .001$), which correctly classified 83.5% of total samples. Likewise in the model using first day measurement of HWIs, the omnibus test revealed significant reliability ($\chi 2$ (1, 42) = 428.306, $p < .001$) and classified 76.4% of the total samples. Using at least three constructed adjusted models, the significant accuracies obtained from them indicated the high reliability of the thesis' conceptual model and employed independent indicators. This further confirms the suitability of the employed HWIs suggested by Weissman et al. (2007) within four comprehensive dimensions of HWIs (volume, throughput, nurse staffing and patient complexity).

3.6 Ethical Considerations

The type of proposed research is based on an episode dataset that was analysed without the consent of the individuals. Accordingly, all data were to be de-identified before the dataset was obtained. 'De-identifying' data involves excluding any information that may identify a patient, such as names, addresses, and any ID or number that can be traceable to a particular patient). In addition, the hospital from which the data was obtained would also remain confidential. This was due to compliance with the ethical approval obtained from the hospital's human research ethics committe. The committe had concerns regarding the

[58] The detailed information about the association of HWIS with a particular type of AEs has been provided in Section 3.8.4: Subgroup analysis of AEs.

exposure of sensitive hospital information (such as rates of AEs) to third parties. Third party groups and individuals are people who are not involved in research activities that would use the hospital information for advertisement, propaganda, or other unrelated activities.

There were several procedures undertaken to ensure that confidentiality risks were carefully monitored and mitigated:

- The datasets were only available to the research team. All datasets were stored in secure areas and on password-protected computers;
- No sensitive and applicable patient-level traceable information (such as ID numbers) was available on the dataset;
- Guarantee was given for the destruction of the dataset two years post completion of this study.

Following the above considerations, ethics approval was obtained from the hospital human research ethics committee. Following approval from the participating hospital, the ethics approval was obtained from the researcher's university[59]. Note that ethics approval is based on effective clincal practice of data mamangement and analytics, as described above, and is governed by the Australian National Statement on Ethical Conduct on Research.

3.7 Data Source

Data were obtained from a metropolitan hospital in Victoria, Australia. The sample included a longitudinal cohort of the first 1,000 de-identified patient episodes (823 medical episodes, 177 surgical episodes[60]) in the order of date of admission, collected between 1st January and 25th May in 2001. The date of this dataset makes the analysis retrospective to a very long time ago; however, based on this thesis' scope, it is succinct for doing what has been proposed in this thesis'. Modern casemix data sets are updated with minor revisions each year, such as adding new DRGs, but essentially the indicators remain the same have. Moreover, new concepts and methodologies are introduced in this thesis which can be validated on this data set.

[59] The ethics letter of approval from Victoria University has been attached in Appendix E.
[60] There was a total of 6 other type DRGs which were not involved with any surgery procedure and were included in non-surgical or medical cohort.

3.8 Data Analysis

The data first was imported to an Access data base. All necessary information such as patient DRG and patient nursing DRG cost weights added to this database. A separate Java application was developed to detect different measurement of exposure to HWIs. Similarly, the proposed approach for identification of AEs from CHADx (Section 3.4) and Charlson comorbid index was implemented in the program to detect each patient's comorbid conditions and AEs respectively[61]. SPSS version 22.0 was the program used for all the statistical analysis. Firstly, the cohort characteristics were obtained from the hospital episode dataset using descriptive statistics. Then, adjusted models of HWIs with AEs were constructed based on an econometric model using this thesis' conceptual model (Table 3.2). The proposed econometric model is described in Section 1.8.2: Adjusted models.

3.8.1 Cohort characteristics

The cohort characteristics of patients were obtained using descriptive statistics. For each continuous independent indicator the mean, median (second interquartile range - IQR) and standard deviation were obtained for the whole cohort. For categorical independent indicators, the frequency and percentage of each category of indicator toward all categories from the whole cohort were obtained. In addition, bivariate analysis was conducted to examine the association of patient characteristic indicators with AEs. This unadjusted bivariate analysis was used to show the association of patient characteristic indicators with AEs regardless of the effect of other independent indicators. For this purpose, since our dependent indicator (patient's AEs) is a binary variable, a Chi-squared test was used for the categorical independent indicators[62]. For continuous independent indicators, firstly, the normality of distribution was acquired by the Shapiro-Wilk test. Subsequently, the Independent Samples t-test and Mann-Whitney U test were used on continuous normal and non-normal distributed indicators, respectively.

[61] Due to ethical considerations, the codes related to this application are not provided in this thesis.

[62] As a part of optimization, if a cell's count value (the number of occurrences or non-occurrences of the independent indicator when either accompanied or not accompanied with the dependent indicator) is less than 5, Fisher's exact test was employed instead of the Chi-squared test.

3.8.2 Adjusted models

The adjusted models of HWIs with AEs were constructed using the proposed conceptual model (Table 3.2) by employing an econometric model[63]. Since the dependent indicator in this thesis was a binary variable representing the likelihood of a patient's AE, an econometric model was established based on a logistic regression. Moreover, there could be other unobservable effects due to the heterogeneity among patients which cannot be explicitly employed in the adjusted model (refer to Chapter 2: Section 2.3.1.3: Ward). To capture all these effects, all HWIs and their random effects within the corresponding adjacent DRGs[64] were employed in the econometric model. As stated previously (3.3.1.2: Patient episode characteristics), in the econometric model the adjacent DRG was employed instead of the DRG as the effect of comorbid condition (input) and AEs (output) have already been included in this thesis' conceptual model. The econometric model was formulated as follows:

$$Log\ AE_{ij} = \alpha_{10} P_{ij} + \beta_{10} W_{ij} + \gamma_{1j} W_{ij} + u_{0j} + e_{ij} \quad (3.1)$$

Where AE_{ij} is the binary variable for occurrences of an AE in patient i belonging to adjacent DRG j. P_{ij} represents patient-related indicators including demographic characteristics (age, sex, admission type), episode characteristics (Adjacent DRG cost weight), number of procedures, date of admission and discharge status) and patient comorbid conditions (refer to Section 3.3.1.2: Patient episode characteristics). W_{ij} represents the employed HWIs (the number of medical and surgical admissions, percentage of emergency admissions, number of patients each day, average DRG cost weight and average nursing DRG cost weight) that patient i is exposed to in the adjacent DRG j. β_{10} represents the coefficient for the fixed effect of HWIs on AEs, while γ_{1j} represents the coefficient of random effects of HWIs on AEs, within adjacent DRGs. u_{0j} represents the adjacent DRG level error term, and e_{ij} represents the patient level error term. Following the above definition, the econometric model was then constructed using the Generalized Linear Mixed Model in SPSS using binomial distribution and the logarithmic link function.

Based on the proposed econometric model shown above (Formula 3.1), adjusted models of HWIs with AE were constructed. The reliability of these models was evaluated against some

[63] An econometric model is a statistical relational model that holds a relationship between the various economic quantities and a particular economic phenomenon (Sims, 1980).

[64] As described in the literature review chapter (Section 2.4: Limitations), the random effect of HWIs due to patients' different DRGs on the increased patient's LOS have been demonstrated by Berry Jaeker and Tucker (2012a). It is possible for this effect to exist for other measurements of patient adverse outcomes such as AEs.

accuracy criteria. These accuracy criteria were obtained by two measurements. One was the percentage of correctly classified samples (overall accuracy). Another was the Akaike Information Criterion (AIC) (Akaike, 1974). Both indicators represent the relative quality of the statistical model if it fits well within the employed hospital episode dataset.

It is notable that the adjustment of HWIs was performed on a comprehensive suite of HWIs in four broad dimensions (volume, throughput, patient intensity, nurse staffing and workload). This full adjustment mitigates the omitted variable bias effect between a HWI and AEs due to neglect of other effective HWIs. Likewise, it reduces the likelihood of spurious associations between employed HWIs in the adjusted model and AEs. In addition, the adjustment was also performed on all random effects of HWIs due to patients' different adjacent DRGs.

Moreover, based on the evaluated conceptual model (refer to Section 3.5: Evaluation of the Proposed Conceptual Model), all patient characteristics were included in the adjusted model. As a result, the effect of each HWI was adjusted by the effect of other patient characteristic indicators that have substantial impact on AEs. This adjustment achieves a true association between a HWI and AEs, since the association was obtained after adjustment by the effect of patient characteristic indicators that have already been shown to have a significant effect on the variation of the likelihood of AEs.

3.8.3 Stratified analysis

The effect of HWIs on patient adverse outcomes can vary based on the type of patients (medical versus surgical patients) involved (Berry Jaeker & Tucker, 2012a; Kiekkas et al., 2008; Schwierz, Augurzky, Focke, & Wasem, 2012). Therefore, two stratified (separate) analyses based on different types of patients were conducted in this thesis. Consequently, results for each type of patient are analysed and discussed separately. To classify each patient as either surgical or medical patients, their compounding DRGs were used. Appendix D provides the list of AR-DRG codes (version 4.2) employed in thesis along with categorization of each code to either medical or surgical patients.

3.8.4 Subgroup analysis of AEs

Subgroup analysis of AEs was undertaken to examine the association of HWIs with the likelihood of each type of AE represented by CHADx major categories. This was done similar to the analyses for all types of AEs by using different adjusted models (Section 3.8.2:

Adjusted models). Three measurements of HWIs, including median and peak of daily values of HWIs during the patient's LOS, and HWIs on the admission day, were employed in the separated analysis. Since AEs are categorized within 17 major CHADx categories, up to 17 subgroup analyses of AEs could have been performed in this study.

The main advantage of the subgroup analysis of AEs lies in the fact that it is possible that the association of a HWI is not significant for all types of AEs, but could be quite significant for a particular type of AE. Therefore, subgroup analysis of AEs can reveal the covert association between HWIs and AEs. In addition, as a result of subgroup analysis of AEs, the effect of different types of AEs (different CHADx categories) on each other is also obtained. In contrast to the aforementioned advantages, the problem with undertaking the subgroup analysis of AEs was that the frequency of AEs was low in some CHADx categories. These low frequencies of CHADx categories are likely to make the adjusted model of HWIs with AEs over-trained (Tibby et al., 2004). To avoid these over-trained models, the subgroup analysis of AE was restricted to models indicating a true positive rate (percentage of correctly classified samples among those having a CHADx AE) for CHADx categories higher than 50%[65].

For the purpose of examining the effect of different types of AEs on each other, the analysis that used the measurement that achieved the highest overall accuracy was chosen. It is important to note that the inclusion of HWIs in any adjusted model for examining the effect of different types of AEs (CHADx categories) on each other was compulsory. HWIs can have significant effects on different CHADx categories when employed as both a dependent indicator and as independent indicators (confounding effect). It follows then that omission of HWIs from the adjusted model leads to a misleading result.

3.8.5 Composite index of patient exposure to HWIs

In the context of this thesis, a composite index is a function created from an adjusted model of HWIs with AEs. This function is expected to increase the accuracy of subsequent adjusted or prediction models that use the index as an additional independent indicator to their dataset. As described in Chapter 2 (Section 2.5: Conclusion), there is no composite index of patient

[65] Based on my evaluations on the current dataset, this percentage needs to be at least 50% to show that a model is well trained. This figure was not suggested in any previous literature and is tentative based on several evaluations on the dataset employed in this thesis.

exposure to HWIs described in the literature. HWIs have a crucial effect on the increased likelihood of patients' AEs (Pedroja, 2008; Pedroja et al., 2014; Weissman et al., 2007). However, the effect of HWIs has been neglected in numerous studies, for example, examining the association of patient characteristics such as comorbid conditions with the likelihood of an AE (Bohensky et al., 2013; Hauck et al., 2012). Therefore, due to the significant effect of HWIs on AEs, the neglect of HWIs in any adjusted model linked to AEs can lead to the omitted variable bias effect of HWIs (Barreto & Frank, 2005) and consequently inaccurate results. To make this index utilizable in any prospective study, it needs to be employedin a cost effective manner and the use of a hospital episode data is more readily obtained than other methods such as audit. This is another justification for why this thesis identifies both HWIs and AEs only from a hospital episode dataset.

This thesis developed a composite index of patient's HWIssby predicting the association of HWIs on the admission day with the likelihood of a patient's AE. A 2-fold cross validation was used to construct and evaluate the index using the existing dataset; 2-fold cross validation divides the dataset into two equal parts ($n_1 = n_2 = 500$ episodes). It then constructs and evaluates the composite index in two iterations using separated training and test datasets. The reason for 2-fold cross validation was that this type of training and evaluation comprises the least number of iterations and the highest proportion of records (50%) for the evaluation dataset. It is expected that the higher proportion of records for the evaluation set results in a more rigorous evaluation of the training index on the evaluation set for each iteration.

To construct the index, a binary logistics regression model was established as a base classifieron the training set for each iteration. The independent indicators in the logistic regression model were selected based on any indicator from the proposed conceptual model (Table 3.2), which were extractable from the time of patient admission[66]. This included both HWIs (exposure to HWIs at the time of patient admission) and the patient's characteristic indicators. The HWIs were all HWIs from the proposed conceptual model (Table 3.2) except 'exposure to hospital patients' DRG' and 'patients' nursing DRG cost weights'. The 'exposure to hospital patient DRG' and 'nursing DRG cost weights' were excluded due to the need to identify and extract DRGs of hospital patients at the time of the patients' discharges

[66] This approach is similar to that used in the development of patient intensity indexes such as APACHE II (Knaus et al., 1985) and SAPS II (Le Gall et al., 1993), which used physiological indicators obtained from the first 24 hours of patient admission for examining their association with the likelihood of patient mortality.

(some were possibly identified beyond the patient's admission date – making it impossible to calculate exposure to hospital DRG and nursing DRG cost weights on the patient's admission date). For the same reason, the indicators 'medical admission' and 'surgical admission' could not be used – as these admissions required patients' DRGs to classify the admission type as medical or surgical; the total number of admissions was used instead. The demographic characteristics indicators were the patient's age, sex, admission type and the date of admission[67]. All categorical indicators were converted to binary variables.

To train the index, the Generalized Linear Model using binomial distribution and logarithmic link function was used in SPSS. An exhaustive search on the search space ($n=2^{15}-1$ (null combination)=32,767) was employed to select an optimized set of indicators that resulted in the highest overall accuracy of the adjusted model. This exhaustive search was implemented using SPSS Integration Plug-in for Java (IBM Corp, 2012)[68]. The indicators obtained as the result of exhaustive search and their coefficients were used to create a function (composite index) linking the patient'sHWIs on the admission day with the likelihood of a patient's AE. This function was then used on the test dataset for the evaluation of the constructed index. It is expected using this function can further improve the accuracy of the adjusted model constructed based on the evaluation dataset.

[67] For the simplicity of the composite index, the comorbid conditions were not included in the construction of the index. Moreover, not all comorbid conditions are defined at the time of patient's admission.
[68] The code related to exhaustive search has been provided in Appendix F.

Chapter 4: Findings

4.1 Introduction

Some of the objectives of this thesis were:

1. To develop a reliable and accurate adjusted model to explore the association of HWIs with AEs.
2. To develop a composite index of HWIs that predicts the likelihood of a patient's AE.
3. To analyse the effect of HWIs on particular types of AEs according to CHADx categories.
4. To examine the effect of different types of AEs (CHADx categories) on each other after adjusting for the effect of HWIs (this is the result of the third objective).

Following the discussion in the previous chapter on the development of adjusted model and the composite index of HWIs, this chapter provides the results of the implementation of the adjusted models of HWIs with AEs (using different measurements), results of the subgroup analysis of AEs, and the proposed approach for establishing the composite index of HWIs.

4.2 Cohort Characteristics

There were 1,000 patient episodes of care[69] included for analysis. As stated in the previous chapter (Chapter 3: Section 3.8.3: Stratified analysis), the effects of HWIs on AEs could vary based on different types of patients; therefore, the total sample was stratified into two samples, namely medical patients and surgical patients. Table 4.1 illustrates the cohort characteristics within the medical, surgical and total samples. In the dataset, there were 823 medical (82.3%) and 177 surgical (17.7%) patients' episodes of care.

[69] It should be noted that throughout this chapter the term 'patient' may be used instead of 'patient episode of care'. However, it would denote a patient's episode of care instead of a patient.

Table 4.1

Dataset Cohort Characteristics.

Patient characteristic indicators		Medical patients ($n_1 = 823$)	Surgical patients ($n_2 = 177$)	Whole sample ($n = 1,000$)
Age		55.2 ± 22.6 (60.1) [a]	46.0 ± 25.1 (41.9)	53.5 ± 23.3 (56.9)
Sex	Male	424 (51.5%)[b]	83 (46.9%)	507 (50.7%)
	Female	399 (48.5%)	94 (53.1%)	493 (49.3%)
Admission type	Casualty and A&E	267 (32.4%)	47 (26.6%)	314 (31.4%)
	Change from psychiatric or psychogeriatric units	2 (.2%)	0 (.0%)	2 (.2%)
	Other - includes referral from local medical officer (LMO)	382 (46.4%)	26 (14.7%)	408 (40.8%)
	Qualified and unqualified new-born	14 (1.7%)	0 (.0%)	14 (1.4%)
	Transfer from other acute hospital external care rehabilitation and geriatric centers	10 (1.2%)	0 (.0%)	10 (1.0%)
	Waiting list	148 (18.0%)	104 (58.8%)	252 (25.2%)
DRG cost weight		.9 ± 1.4 (.5)	1.7 ± 1.6 (.9)	1.0 ± 1.4 (.6)
Number of procedures		2.0 ± 1.5 (2.0)	3.2 ± 1.7 (3.0)	2.2 ± 1.6 (2.0)
Day of week	Day before / after weekends	273 (33.2%)	73 (41.2%)	346 (34.6%)
	Weekdays	415 (50.4%)	85 (48.0%)	500 (50.0%)
	Weekends	135 (16.4%)	19 (10.7%)	154 (15.4%)
Discharge status	Change to psychiatric or psychogeriatric units	2 (.2%)	0 (.0%)	2 (.2%)
	Change to designated rehab program/unit levels	1 (.1%)	0 (.0%)	1 (.1%)
	Change to Nursing Home Transition (NHT)	3 (.4%)	0 (.0%)	3 (.3%)
	Death	13 (1.6%)	2 (1.1%)	15 (1.5%)
	Discharge to home without support	724 (88.0%)	158 (89.3%)	88.4 (88.4%)

	Left against medical advice	7 (.9%)	0 (.0%)	7 (.7%)
	Other formal separation	2 (.2%)	1 (.6%)	3 (.3%)
	Transfer to nursing home	7 (.9%)	0 (.0%)	7 (.7%)
	Transfer to other acute hospitals/external care facilitates/rehabilitation and geriatric centers	64 (7.8%)	16 (9.0%)	80 (8.0%)
Charlson comorbid conditions	AIDS/HIV	0 (.0%)	0 (.0%)	0 (.0%)
	Cerebrovascular disease	15 (1.8%)	1 (.6%)	16 (1.6%)
	Chronic pulmonary disease	14 (1.7%)	1 (.6%)	15 (1.5%)
	Congestive heart failure	7 (.9%)	0 (.0%)	7 (.7%)
	Dementia	8 (1.0%)	0 (.0%)	8 (.8%)
	Diabetes with chronic complication	7 (.9%)	4 (2.3%)	11 (1.1%)
	Diabetes without chronic complication	3 (.4%)	0 (.0%)	3 (.3%)
	Hemiplegia or paraplegia	3 (.4%)	1 (.6%)	4 (.4%)
	Mild liver disease	4 (.5%)	0 (.0%)	4 (.4%)
	Malignancies including lymphoma and leukemia except malignant neoplasm of skin	112 (13.6%)	14 (7.9%)	126 (12.6%)
	Metastatic solid tumor	7 (.9%)	0 (.0%)	7 (.7%)
	Moderate or severe liver disease	1 (.2%)	0 (.0%)	1 (.1%)
	Myocardial infarction	6 (.7%)	0 (.0%)	6 (.6%)
	Other (no comorbid conditions)	603 (73.3%)	154 (87.0%)	757 (75.7%)
	Peptic ulcer	8 (1.0%)	0 (.0%)	8 (.8%)
	Peripheral vascular disease	2 (.2%)	2 (1.1%)	4 (.4%)
	Renal disease	15 (1.8%)	0 (.0%)	15 (1.5%)
	Rheumatic disease	8 (1.0%)	0 (.0%)	8 (.8%)

Note. [a]Data presented as mean ± standard deviation (median) for continuous indicators.

[b]Data presented as number of episodes (%) for categorical indicators. The percentages are ratio of each category to the all patients in each sample cohort.

As shown in Table 4.1, the total sample has a mean age of 53.5 years (*SD* = 23.3). The percentage of male patient episodes of care was slightly higher than the percentage of females in medical (51.5% male versus 48.5% female) and total samples (50.7% versus 49.3%), while it was lower in the surgical sample (46.9% versus 53.1%). The most common cause of admission was 'Other - includes referral from local medical officer (LMO)' within the medical (46.4%), surgical (14.7%) and the total samples (40.8%). In addition, patients were mostly admitted on weekdays (50.0%) and mostly discharged to home without any support (88.4%). Most of the patients in the sample did not have any comorbid condition (75.7%), however, among those who had comorbid conditions (medical 26.7%, surgical 12.9%), 'malignancies including lymphoma and leukemia except malignant neoplasm of skin' was the most frequent comorbid condition (12.6%).

4.3 Cohort Characteristic Indicators and AEs

Out of the total sample (n = 1,000 patient episodes), in 213 episodes (21.3%) there were 294 incidents of AEs[70]. Among these incidents, 238 incidents were within the medical patient sample (n_1=178 episodes, 21.6% of medical sample) and 56 incidents were within the surgical patient sample (n_2= 35 episodes, 19.7% of surgical sample). This number of AEs resulted in the rate of 140, 99, and 131 AEs per 1,000 inpatient days within medical, surgical, and the total patient samples, respectively. The independent effect of cohort characteristic indicators on AEs was obtained using bivariate analyses (an unadjusted model). For this purpose, the chi-square test was employed for categorical indicators, while the Independent Samples t-test and Mann-Whitney U test were employed for normally and non-normally distributed independent continuous indicators, respectively. Evidence of the relationship of cohort characteristics with AEs is provided in Table 4.2.

[70] This indicates some patient episodes have more than one incident of AEs.

Table 4.2

Association of Patient Characteristic Indicators with AEs.

Patient characteristic indicators		**Medical patients ($n_1 = 823$)**		**Surgical patients ($n_2 = 177$)**	
		Patients without AE ($n_{1,1} = 645$)	Patients with an AE ($n_{1,2} = 178$)	Patients without AEs ($n_{2,1} = 142$)	Patients with an AE ($n_{2,2} = 35$)
Age		54.4 ± 21.5 (57.6) [a]	58.0 ± 26.1 (68.9) ** ‡	42.8 ± 23.6 (40.2)	58.9 ± 26.8 (58.7) **
Sex	Male	327 (50.7%)[b]	97 (54.5%)	61 (43.0%)	22 (62.9%)*
	Female	318 (49.3%)	81 (45.5%)	81 (57.0%)	13 (37.1%)
Admission Type	Casualty and A&E	188 (29.1%)	79 (44.4%)**	29 (20.4%)	18 (51.4%)**
	Change from psychiatric or psychogeriatric units	1 (.2%)	1 (.6%)	-†	-
	Other - includes referral from local medical officer	308 (47.8%)	74 (41.6%)	17 (12.0%)	9 (25.7%)*
	Qualified and unqualified new-born	4 (.6%)	10 (5.6%)*	-	-
	Transfer from other acute hospital external care rehabilitation and geriatric centres	4 (.6%)	6 (3.4%)**	-	-
	Waiting list	140 (21.7%)	8 (4.5%)**	96 (67.6%)	8 (22.9%)**
DRG cost weight		.7 ± .7 (.5)	1.4 ± 2.5 (.9)**	1.2 ± .9 (.8)	3.7 ± 2.3 (3.3)**
Number of procedures		1.8 ± 1.2 (2.0)	2.6 ± 2.2 (2.0)**	2.8 ± 1.1 (3.0)	4.7 ± 2.7 (4.0)**
Day of week	Day before / after weekends	204 (31.6%)	69 (38.8%)	61 (43.0%)	12 (34.3%)
	Weekdays	335(51.9%)	80(44.9%)	74(52.1%)	11(31.4%)*
	Weekends	106(16.4%)	29(16.3%)	7(4.9%)	12(34.3%)**
Discharge status	Change to psychiatric or psychogeriatric units	2(.3%)	0(.0%)	-	-
	Change to designated rehab program/unit levels	1(.2%)	0(.0%)	-	-

	Change to Nursing Home Transition (NHT)	0(.0%)*	3(1.7%)*	-	-
	Death	6(.9%)*	7(3.9%)	0(.0%)	2(5.7%)*
	Discharge to home without support	588(91.2%)	136(76.4%)**	135(95.1%)	23(65.7%)**
	Left against medical advice	7(1.1%)	0(.0%)		
	Other formal separation	0(.0%)	2(1.1%)*	1(.7%)	0(.0%)
	Transfer to nursing home	2(.3%)	5(2.8%)**	-	-
	Transfer to other acute hospitals/external care facilitates/rehabilitation and geriatric centres	39(.6%)	25(14.0%)	6(4.2%)	10(28.6%)**
Charlson comorbid conditions	AIDS/HIV	-	-	0(.0%)	0(.0%)
	Cerebrovascular disease	12(1.9%)	3(1.7%)	1(.7%)	0(.0%)
	Diabetes with chronic complication	6(.9%)	1(.6%)	3(2.1%)	1(2.9%)
	Chronic pulmonary disease	12(1.9%)	2(1.1%)	1(.7%)	0(.0%)
	Congestive heart failure	4(.6%)	3(1.7%)	-	-
	Dementia	5(.8%)	3(1.7%)	-	-
	Hemiplegia or paraplegia	1(.2%)	2(1.1%)	0(.0%)	1(2.9%)
	Mild liver disease	3(.5%)	1(.6%)	-	-
	Malignancies including lymphoma and leukemia except malignant neoplasm of skin	98(15.2%)	14(7.9%)*	11(7.7%)	3(8.6%)
	Metastatic solid tumor	6(.9%)	1(.6%)	-	-
	Myocardial infarction	5(.8%)	1(.6%)	-	-
	Other	460(71.3%)	143(80.3%)*	126(88.7%)	28(80.0%)
	Peptic ulcer	8(1.2%)	0(.0%)	-	-
	Peripheral vascular disease	0(.0%)	2(1.1%)	0(.0%)	2(5.7%)*
	Renal disease	15(2.3%)	0(.0%)	-	-

	Rheumatic disease	8(1.2%)	0(.0%)	-	-
	Moderate or severe liver disease	1(.2%)	0(.0%)	-	-
	Diabetes without chronic complication	1(.2%)	2(1.1%)	-	-

Note. [a]Data presented as mean ± standard deviation (median) for continuous indicators.

[b]Data presented as number (%) for categorical indicators. The percentages are ratio of each category to the patients in each sample cohort.

‡*Indicates significant differences between mean values of the corresponding indicator between patients with an AE and those without an AE*.

** $p < .01$, * $p < .05$.

†No statistics computed.

Association of cohort characteristic indicators with AEs are shown in Table 4.2. Patients with AEs have higher average ages within both the medical (58.0 vs 54.4, *Mann-Whitney U* = 49,222.00, $p = .004$) and surgical samples (58.9 vs 42.8, *Mann-Whitney U* = 1,583.00, $p < .001$). In addition, the average of patients' DRG cost weight was significantly higher in patients with an AE compared to those without an AE, within both the medical (1.4 vs .7, *Mann-Whitney U* = 45,277.00, $p < .001$) and surgical samples (3.7 vs 1.2, *Mann-Whitney U* = 705.50, $p < .001$). Similarly, the average of patients' number of procedures was significantly higher when patients have an AE in both medical (2.6 vs 1.8, *Mann-Whitney U* = 46,976.50, $p < .001$) and surgical samples (4.7 vs 2.8, *Mann-Whitney U* = 1,132.00, $p < .001$).

Additionally, in the surgical sample, male patients had a significantly higher likelihood of an AE (62.9% vs 43.0% between males and females, $\chi 2$ (1, N = 2,730) = 23.41, $p = .035$). Furthermore, in comparison to other types of admissions[71], patients with Casualty and A&E admissions had a significantly higher likelihood and frequency of AEs within both the medical (44.4% vs 29.1%, $\chi 2$ (1, N = 823) = 14.77, $p < .001$) and surgical samples (51.4% vs 20.4%, $\chi 2$ (1, N = 177) = 13.84, $p < .001$). Furthermore, surgical patients admitted on weekends versus weekdays had a significantly higher likelihood and frequency of AEs than those admitted on weekdays (34.3% vs 4.9%, $\chi 2$ (1, N = 177) = 25.25, $p < .001$). However, the bivariate analyses revealed no significant effect of the presence of any comorbid condition on higher frequencies of AEs.

4.4 Patient Exposure to HWIs and AEs

The association of HWIs (patient exposure to HWIs) with AEs was obtained using three measurements. These measurements were median and peak of daily HWI values during the patient's entire LOS, and HWIs on the day of admission. Stratified analysis was conducted based on both medical and surgical samples since the effect of HWIs on AEs can vary based on the different types of patients involved. A generalized mixed model (refer to Chapter 3, Section 3.8.2: Adjusted models) was established based on all fixed and random effects of HWIs. The model corresponding to medical patients reached the AIC = 801 and overall accuracy of 82.3%. In surgical patients, the model reached an AIC = 9,169 and overall accuracy = 75.7%. It is notable that the random effects of medical admissions in the medical

[71] The comparisons were done using Chi-squared test comparing the patients having a Casualty and A&E admission with other types of admissions on the likelihood of an AE.

patient sample model were significant (*Wald Z* = 3.102, p = .036)[72]. Table 4.3 provides the estimates of coefficients of HWIs from the medical and surgical patients' models related to fixed effects of HWIs.

Table 4.3

Median of Daily Values of HWIs During the Patient's Entire LOS and AEs.

HWIs†	**Medical patients (n_1= 823)**			**Surgical patients (n_2= 177)**		
	Coefficient	95% confidence intervals		Coefficient	95% confidence intervals	
		Lower	Upper		Lower	Upper
Number of medical admissions¶	.804	.723	.885	.615	.353	.877
Number of surgical admissions	.211	.002	.420	.212	.062	.362
Percentage of emergency admissions	.087	.011	.163	.102	.009	.195
Number of discharges	-.446	-1.303	.411	-.021	-.145	.103
Number of patients	1.132*	.023	2.241	.701	.406	.996
Average of patients' DRG cost weights	.475	.122	.828	.343	.013	.673
Average of patients'nursing DRG cost weights	-.901	-1.212	-.590	-.189	-.203	-.175

*Note. * p < .05 (The p-value for each coefficient tests the null hypothesis that the coefficient is equal to zero or have no effect).*

†The models were further adjusted using other indicators including: 1-Age 2-Sex 3-Admission type 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions).

¶ The random effect of the numbers of medical admissions was included in the medical patients model.

It is apparent from Table 4.3 that within the medical patient cohort, exposure to a higher number of patients (bed occupancy) significantly increased the likelihood of an AE (β = 1.132, p < .05, 95% CI [.023, 2.241]). However, no significant association was identified for other HWIs. Similarly, in the surgical patient cohort, no HWIs (using median measurement) had a significant effect on the increased likelihood of a patient's AE.

Similar procedures were undertaken to analyse the effect of exposure to peak daily values of HWIs, during the patient's LOS, for the likelihood of a patient's AE. The adjusted model for

[72] The Wald Z null hypothesis assumes that the variance estimate for random effect is zero or the random effect is not significant enough to be included into the model.

medical patients reached an AIC of 406 and overall accuracy of 86.3%. For surgical patients, the model reached an AIC of 2,952 and overall accuracy of 81.3%. It is notable in the medical patient sample; the random effect of medical admission within DRGs was significant (*Wald Z* = 1.04, $p < .01$). Table 4.4 provides the coefficients' estimates obtained from the medical and surgical patient models.

Table 4.4

Peak of Daily Values of HWIs During the Patient's LOS and AEs.

HWIs†	**Medical patients (n_1= 823)**			**Surgical patients (n_2= 177)**		
	Coefficient	95% confidence intervals		Coefficient	95% confidence intervals	
		Lower	Upper		Lower	Upper
Number of medical admissions¶	1.014*	.718	1.311	.612	.405	.819
Number of surgical admissions	.756	.483	1.029	.215	.062	.368
Percentage of emergency admissions	.210	.023	.397	.067	-.047	.181
Number of discharges	-.029	-.126	.068	.325	.108	.542
Number of patients	2.148**	1.353	2.943	1.106*	.844	1.368
Average of patients' DRG cost weights	.789	.551	1.027	-.349	-.526	-.172
Average of patients' nursing DRG cost weights	-.265	-.543	.013	.045	-.056	.146

*Note. ** $p < .01$.*

** $p < .05$.*

†The models were further adjusted using other indicators including: 1-Age 2-Sex 3-Admission type 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions).

¶The random effect of the number of medical admissions was included in the medical patient model.

Higher values of HWIs (when examined by peak of daily values), led to a significant increase in the likelihood of a patient's AE. For example, in medical patients, a higher number of medical admissions (β = 1.014, $p < .05$, 95% CI [.718, 1.311]), and number of patients (β = 2.148, $p < .001$, 95% CI [1.353, 2.943]) were associated significantly with an increased likelihood of a patient's AE. Moreover, in the surgical patient sample, a higher number of patients was significantly associated with an increased likelihood of a patient's AE (β = 1.106, $p < .05$, 95% CI [.844, 1.368]).

Analyses were further repeated for the effect of HWIs on the day of admission, on the likelihood of a patient's AE. However, the models related to both the medical and surgical samples (overall accuracy – medical sample = 79.6%, surgical sample = 82.4%) did not represent any significant association between higher values of any HWIs on the day of admission, and an increased likelihood of a patient's AE[73]. Table 4.5 shows the coefficients related to these models.

Table 4.5

HWIs at the Time of Patient's Admission and AEs.

HWIs†	**Medical patients (n_1= 823)**			**Surgical patients (n_2= 177)**		
	Coefficient	95% confidence intervals		Coefficient	95% confidence intervals	
		Lower	Upper		Lower	Upper
Number of medical admissions	.031	-.063	.124	-.114	-.218	-.010
Number of surgical admissions	-.014	-.177	.148	.204	.023	.385
Percentage of emergency admissions	.008	-.103	.119	.526	.237	.815
Number of discharges	.007	-.094	.107	.053	.002	.104
Number of patients	.012	-.053	.079	.050	.023	.077
Average of patients' DRG cost weights	.050	-.698	.797	-.903	-1.506	-.300
Average of patients' nurisng DRG cost weights	-.085	-1.325	1.155	.114	.028	.207

*Note. ** $p < .01$.*

** $p < .05$.*

†The models were further adjusted using other indicators including: 1-Age 2-Sex 3-Admission type 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions).

Figures 4.1 and 4.2 show the summary of findings of this thesis on the association of HWIs with all types of AEs in medical and surgical samples, respectively.

[73] The models using the HWIs at the time of admission in both the medical and surgical samples did not represent any significant random effect of HWIs ($p > .05$).

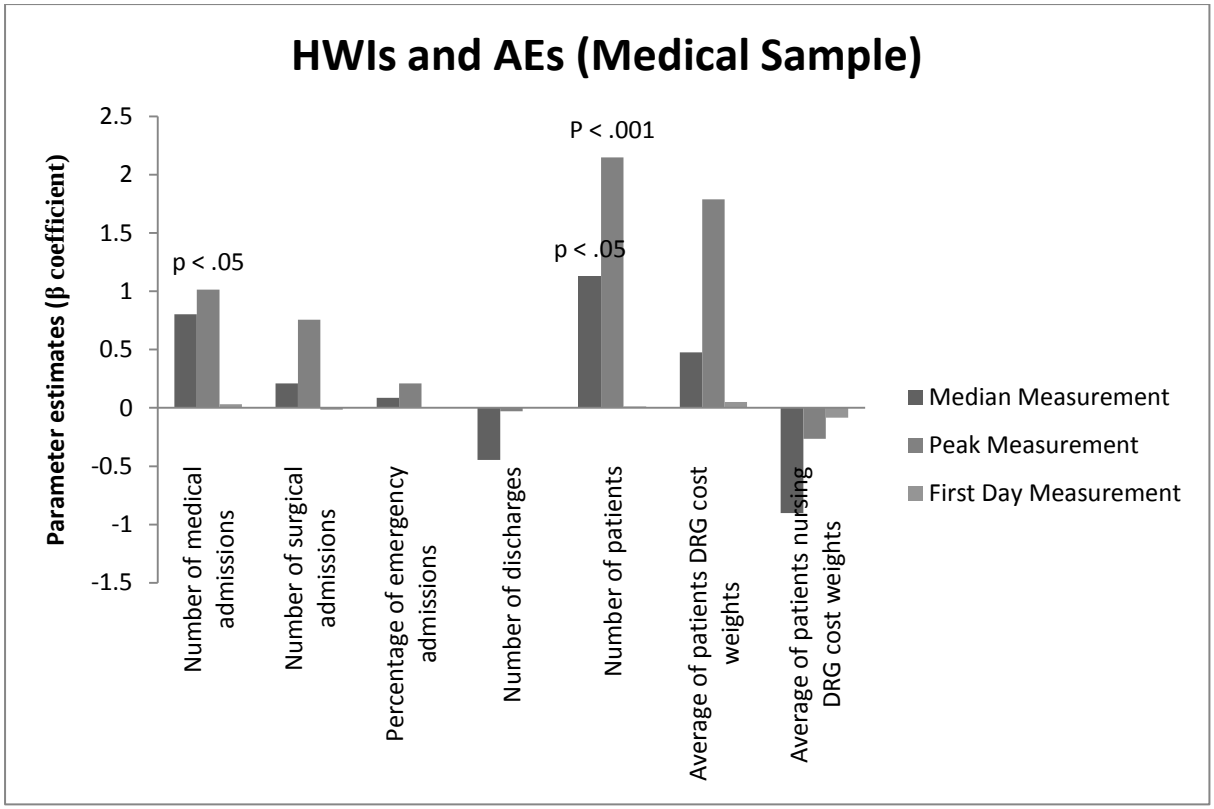


Figure 4.1 Association of HWIs with AEs (Medical Sample).

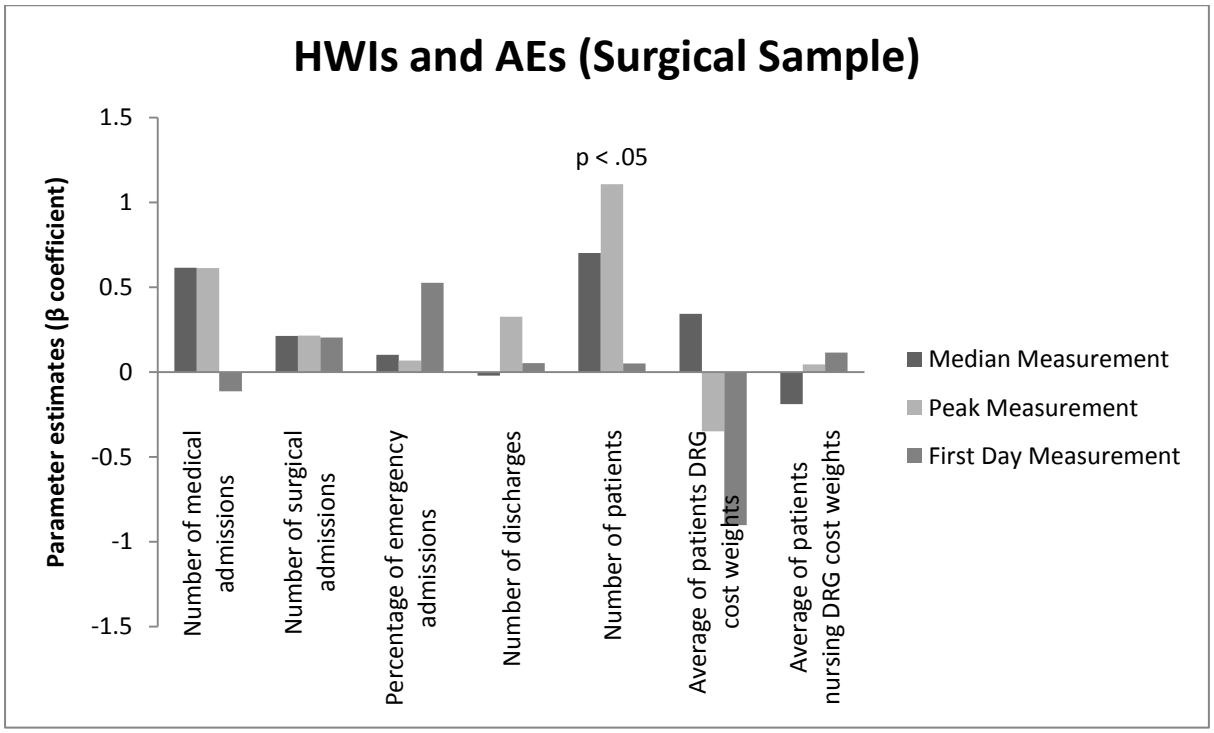


Figure 4.2 Association of HWIs with AEs (Surgical Sample).

According to Figures 4.1 and 4.2, the key findings are:

- The effect of HWIs, when measured by peak measurement is more substantial on increased likelihood of AEs in comparison to other measurements such as median and first day measurements.
- The effect of HWIs on AEs is more evident in medical patients.
- Among different HWIs, the effect of higher hospital numbers of patients (bed occupancy) on increased likelihood of AEs is more substantial in comparison to other HWIs.

The above findings and conclusion are discussed in detail in the following section (Section 4.7: Discussion and Conclusion).

4.5 Subgroup Analysis of AEs

The association of HWIs with all types of AEs were analysed and examined in the previous section. However, this association can be quite different when AEs are confined to a particular type (CHADx category). Subgroup analysis of AEs examines the association of HWIs with a particular type of AE. This subgroup analysis of AEs can identify any covert effects of HWIs on AEs. This covert effect emerges when in contrast to all types of AEs, the effect of HWIs are significant on a particular type of AE. Table 4.6 shows the frequencies of different CHADx categories for both medical and surgical samples.

Table 4.6

Frequencies of Patients' Episodes of Care Having Different CHADx Categories.

CHADx major categories	Medical patients (n_1= 823)¶			Surgical patients (n_2= 177)		
	Patients without AE	Patients with AE	Number of incidents	Patients without AE	Patients with AE	Number of incidents
CHADx 1: Post procedural complications	818(99.4%)[a]	15(1.9%)	15	172(97.2%)	5(2.8%)	5
CHADx 2: Adverse drug events	811(98.5%)	17(2.0%)	17	175(98.9%)	2(1.1%)	2
CHADx 3: Accidental injuries	807(98.1%)	16(1.9%)	17	168(94.9%)	9(5.1%)	9
CHADx 4: Specific infections	818(99.4%)	5(.6%)	5	176(99.4%)	1(.6%)	1
CHADx 5: Cardiovascular complications	805(97.8%)	18(2.2%)	19†	171(96.6%)	6(3.4%)	6
CHADx 6: Respiratory complications	811(98.5%)	12(1.5%)	12	177(100.0%)	0(.0%)	0
CHADx 7: Gastrointestinal complications	806(97.9%)	17(2.1%)	17	174(98.3%)	3(1.7%)	3
CHADx 8: Skin conditions	816(99.1%)	12(1.5%)	12	177(100.0%)	0(.0%)	0
CHADx 9: Genitourinary complications	777(94.4%)	26(3.1%)	26	172(97.2%)	5(2.8%)	6†
CHADx 10: Hospital-acquired psychiatric states	813(98.8%)	10(1.2%)	10	176(99.4%)	1(.6%)	1
CHADx 11: Early pregnancy complications	823(100.0%)	0(.0%)	0	177(100.0%)	0(.0%)	0
CHADx 12: Labour, delivery & postpartum complications	811(98.5%)	12(1.5%)	12	172(97.2%)	5(2.8%)	5
CHADx 13: Perinatal complications	811(98.5%)	12(1.5%)	12	177(100.0%)	0(.0%)	0
CHADx 14: Hematological disorders	799(97.1%)	24(2.9%)	24	169(95.5%)	8(4.5%)	8
CHADx 15: Metabolic disorders	812(98.7%)	11(1.3%)	11	174(98.3%)	3(1.7%)	3
CHADx 16: Nervous system complications	816(99.1%)	7(.9%)	7	175(98.9%)	2(1.1%)	2
CHADx 17: Other complications	801(97.3%)	22(2.7%)	22	172(97.2%)	5(2.8%)	5
All categories	645(78.4%)	178(21.6%)	238	142(80.2%)	35(19.8%)	56

Note. [a]Data presented as number of patient episodes (%). Percentages are ratio of total episodes in each CHADx category to the total number of patients (episodes) in the corresponding sample.

¶Data in brackets represents the number of patient episodes.

†Some patients' episodes can have more than one number of AE incidents.

As illustrated in Table 4.6, the majority of medical patients with an AE had a CHADx 9 AE (14.6%); while in surgical patients, the majority of patients with an AE had a CHADx 3 AE (25.7%).

In this thesis, the analyses for subgroup analyses of AEs were only done based on CHADx 9 (genitourinary complications) and CHADx 5 AEs (cardiovascular complications) within the medical patient sample. This was because of the poor calibration of adjusted models that achieved a true positive rate (percentage of correctly classified samples among those having a CHADx AE) of less than 50% for occurrences of CHADx AEs. Poor calibration of CHADx categories indicated these models were not adequately trained to represent the association between HWIs and CHADx AEs. Moreover, some models did not even meet the convergence criteria for an estimate of parameter coefficients due to the low frequencies of occurrences of CHADx categories[74]. Therefore, these models could not be trained because of the low frequency of CHADx categories.

Analysis on the association of HWI with the likelihood of a patient's CHADx 5 or CHADx 9 was undertaken in a similar way to the analysis on the association of HWIs with all types of AEs. Among three measurements of HWIs, only the utilization of HWIs by peak values revealed significant effect of HWIs on the increased likelihood of a patient's CHADx 5 or CHADx 9 AE. Table 4.7 provides the estimates of coefficients obtained from the corresponding medical patient model[75].

[74] The maximum error for reaching a stable value for parameter estimates was set to the SPSS default value (1E-6).
[75] Table 4.7 shows the employed HWIs for medical patient final model related to CHADx 5 (overall accuracy= 83.6%) and CHADx 9 (overall accuracy=86.9%).

Table 4.7

The Peak of Daily Values of HWIs During the Patient's Entire LOS and CHADx 5 and CHADx 9 AEs.

HWIs	**CHADx 5†** **(cardiovascular AEs)**			**CHADx 9 ǂ** **(genitourinary AEs)**		
	Medical patients (n_1 = 823)			Medical patients (n_1 = 823)		
	Coefficient	95% confidence intervals		Coefficient	95% confidence intervals	
		Lower	Upper		Lower	Upper
Number of medical admissions	.818	.512	1.124	.436	.122	.750
Number of surgical admissions	.032	-.056	.121	-.221	-.283	-.159
Percentage of emergency admissions	.236	.125	.347	1.913*	.404	3.422
Number of discharges	.569	.227	.911	.452	.127	.777
Number of patients	.910*	.206	1.614	.403	.243	.563
Average of patients' DRG cost weights	.506	.105	.907	.428	.162	.694
Average of patients' nursing DRG cost weights	-.103	-.305	.099	-.325	-.782	.132

*Note. ** p < .01.*

** p < .05.*

†The corresponding model was adjusted using other indicators including: 1-Age 2-Sex 3-Admission source 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions) 8-CHADx categories (CHADX 1 - 17 except CHADx 5).

ǂThe corresponding model was adjusted using other indicators including: 1-Age 2-Sex 3-Admission source 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions) 8-CHADx categories (CHADX 1 - 17 except CHADx 9).

As shown in Table 4.7, in medical patients, there was a significant association between a higher number of patients (bed occupancy) and an increased likelihood of a patient's cardiovascular AE (CHADx 5) (β = .910, p < .05, 95% CI [.206, 1.614]). Likewise, a significant association between a higher percentage of emergency admissions (in the total of admission) and an increased likelihood of a patient's genitourinary AE (CHADx 9) was revealed (β = 1.913, p < .01, 95% CI [.404, 3.422]).

The effect of other CHADx categories on the likelihood of a patient's CHADx 5 or CHADx 9 AE was obtained using the peak measurement of HWIs for both CHADx categories in the medical sample. Table 4.8 shows the estimates of coefficients related to the likelihood of other CHADx categories affecting a (medical) patient's CHADx 5 and CHADx 9 AEs separately.

Table 4.8

Effect of Other CHADx Categories on CHADx 5 and CHADx 9 AEs.

CHADx major categories†	CHADx 5† (cardiovascular AEs)			CHADx 9 ǂ (genitourinary AEs)		
	Medical patients (n_1 = 823)			Medical patients (n_1 = 823)		
		95% confidence intervals			95% confidence intervals	
	Coefficient	Lower	Upper	Coefficient	Lower	Upper
CHADx1- Post procedural complications	10.104*	6.538	13.670	3.123	1.304	4.942
CHADx2- Adverse drug events	7.612	4.223	11.001	4.558	.729	8.387
CHADx3- Accidental injuries	2.028	-.065	4.121	4.429	1.228	7.630
CHADx4- Specific infections	3.108	.620	5.596	3.546	1.227	5.775
CHADx5- Cardiovascular complications	-§	-	-	5.123*	3.918	6.328
CHADx6- Respiratory complications	3.108	1.129	5.087	2.288	.285	4.291
CHADx7- Gastrointestinal complications	3.922	-7.118	14.962	3.017	1.577	4.457
CHADx8- Skin conditions	.987	-1.104	3.078	-5.217	-10.017	-.417
CHADx9- Genitourinary complications	.876	.093	1.659	-§	-	-
CHADx10- Hospital-acquired psychiatric states	3.254	.096	6.412	3.436	2.579	4.293
CHADx11- Early pregnancy complications	8.129	6.109	10.149	4.363	.094	8.632
CHADx12- Labour, delivery & postpartum complications	7.311	5.011	9.611	.224	-3.106	3.554
CHADx13- Perinatal complications	2.135	.801	3.469	-.126	-.318	.066
CHADx14- Hematological disorders	1.201	.118	2.284	6.548**	4.774	8.322
CHADx15- Metabolic disorders	2.127	.408	3.846	3.761	1.898	5.624
CHADx16- Nervous system complications	-1.150	-6.108	3.808	.448	.129	.767
CHADx17- Other complications	2.805	.124	5.486	2.395	.704	4.086

*Note. ** $p < .01$.*

** $p < .05$.*

†The corresponding model was adjusted using other indicators including: 1-Age 2-Sex 3-Admission source 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions) 8-CHADx categories (CHADX 1 - 17 except CHADx 5).

ǂThe corresponding model was adjusted using other indicators including: 1-Age 2-Sex 3-Admission source 4-DRG cost weight 5-Number of procedures 6- Date of admission (day of the week) 6- Discharge status 7-Comorbid conditions (17 Charlson comorbid conditions) 8-CHADx categories (CHADX 1 - 17 except CHADx 9).

§Indicator was omitted from the model.

As shown in Table 4.8, in medical patients, an existence of a CHADx1 (post procedural complication) (β = 10.104, $p < .05$, 95% CI [6.538, 13.670]) was significantly associated with an increased likelihood of a patient's CHADx 5 AE. Additionally, investigation revealed the presence of a CHADx 5 - cardiovascular AE (β = 5.123, $p < .05$, 95% CI [3.918, 6.328]) and CHADx 14 - hematological disorders (β = 6.548, $p < .01$, 95% CI [4.774, 8.322]) were significantly associated with an increased likelihood of a patient's CHADx 9 AE.

4.6 Composite Index of Patient Exposure to HWIs

One of the objectives of this thesis was to establish a composite index of patient exposure to HWIs that predicts the likelihood of occurrence of an AE (refer to Section 1.6: Aims and Objectives). For this purpose, the patient exposure to HWIs on the admission day was utilized to predict the likelihood of a patient's AE occurring during the patient's entire LOS. The composite index was trained and evaluated using 2 – fold cross validation ($n_1 = n_2 = 500$). As a result, there were two iterations for training and evaluation of the composite index. On each iteration, and on the training set, a binary logistic regression model was used to construct the composite index based on all independent indicators extractable from the day of admission[76]. The binary logistic regression model was then optimized using an exhaustive search to select an optimized set of indicators resulting in the highest overall accuracy (percentage of corrected classified samples).

[76] It included the demographic characteristics indicators such as the patient's age, sex, admission type and the date of admission in addition to exposure to HWIs such as number of admissions (medical and surgical), number of discharges, percentage of emergency admissions and number of patients on the patient's admission day. It is suggested readers refer to Chapter 3 (Section 3.8.5: Composite index of patient exposure to HWIs) for detailed information regarding the construction of the composite index.

On the first iteration *($i = 1$)*, the exhaustive search revealed the final model that had the highest overall accuracy of 86.2%. Table 4.9 shows the corresponding indicators and their coefficients obtained from this iteration.

Table 4.9

Composite Index of Patient Exposure to HWIs, Estimates of Coefficients, ($i = 1$).

Indicators	**Coefficient**	**95% confidence intervals**	
		Lower	**Upper**
Percentage of emergency admissions	-.060	-.432	.312
Number of patients	.519**	.225	.813
Age	.032	-.060	.124
Sex = female	.429*	.209	.649
Admission type = Casualty and A&E	.096	-.235	.427

*Note. ** $p < .01$.*

** $p < .05$.*

From the above table, the likelihood of occurrences of an AE is calculated as follows:

$$\begin{aligned}\text{Log}\, AE = \; & .220 * (Percentage\ of\ emergency\ admissions) + \; .519 \\ & * (Number\ of\ patients) + \; .032 * (Age) + .429 * (Sex \\ & = female) + \; .096 \\ & * (Admission\ type = casualty\ and\ accidental\ emergency)\end{aligned} \quad (4.1)$$

Therefore, the index is formulated as follow:

$$AE = .870^{(Percentage\ \ of\ emergency\ \ admissions\ )} * 3.303^{(Number\ \ of\ patients\ )} * 1.076^{(Age)} * 2.685^{(Sex\ =female\ )} * 1.247^{(Admission\ \ type\ =casualty\ \ and\ \ accidental\ \ emergency\ )} \quad (4.2)$$

Following this, the second half of the dataset (test dataset) ($n_2 = 500$) was used to evaluate the constructed composite index. A binary logistic regression model was established using all possible independent indicators at the time of admission. The model reached an overall accuracy (percentage of correctly classified samples) of 79.8%. The constructed index (Formula 4.2) was then used to add an extra field to the previous model ($n_2 = 500$). Consequently, by establishing another binary logistics regression model, a higher overall accuracy of 84.4% was obtained.

Similar to the first iteration, the index was constructed and evaluated on the second iteration. Table 4.10 shows the obtained indicators and their corresponding estimates of coefficients after the construction of the index on the second iteration *($n_2 = 500$).*

Table 4.10

Composite Index of Patient Exposure to HWIs, Estimates of Coefficients ($i = 2$).

Indicators	**Coefficient**	**95% confidence intervals**	
		Lower	**Upper**
Number of admissions	.147	.023	.271
Percentage of emergency admissions	-.159	-.501	.183
Age	.464	-2.248	3.177
Day of week = weekends	.125	.019	.231
Admission type = Casualty and A&E	.245	-1.119.	1.609

From the above table, the likelihood of occurrences of an AE is calculated as follows:

$$\begin{aligned}\text{Log}\, AE = {} & .147 * (Number\ of\ admissions) + -.159 \\ & * (Percentage\ of\ emergency\ admissions) + .464 * (age) + .125 \\ & * (Day\ of\ week = weekends) + .245 \\ & * (Admission\ type = casualty\ and\ accidental\ emergency)\end{aligned} \quad (4.3)$$

Therefore, the index is formulated as follows:

$$\begin{aligned}AE = {} & 1.402^{(Number\ of\ admissions)} *.693^{(Percentage\ of\ emergency\ admissions)} \\ & * 2.910^{(Age)} * 1.333^{(Day\ of\ week\ = weekends)} \\ & * 1.757^{(Admission\ type\ = casualty\ and\ accidental\ emergency)}\end{aligned} \quad (4.4)$$

Using the test dataset ($n_1 = 500$) on the second iteration ($i = 2$) and using indicators at the time of admission, an overall accuracy of 86.4% was obtained. However, by adding the constructed index (Formula 4.4) a slightly lower overall accuracy of 85.8% was obtained. Overall, based on the two iterations ($i = 1, 2$) and on the whole dataset ($n = 1{,}000$) the overall accuracy on the prediction of AEs was improved by 2.0%. Therefore, based on the employed dataset, this improvement can suggest the effectiveness of the proposed approach (using exhaustive search method) for the construction of a composite index of patient exposure to HWIs at the time of admission to predict the likelihood of a patient's AE. As a

result, the above method (utilization of exhaustive search based on a logistic regression model) can be applied on the whole dataset ($n = 1{,}000$) to obtain a composite index.

Table 4.11

Composite Index of Patient Exposure to HWIs, Estimates of Coefficients (n= 1,000).

Indicators	**Coefficient**	**95% confidence intervals**	
		Lower	**Upper**
Number of admssions	.223	.109	.337
Number of patients	.409	.233	.585
Age	.137	.094	.180
Sex = female	.387	.212	.562
Admission type = Casualty and A&E	.116	.045	.187

From the above table, the likelihood of occurrences of an AE is calculated as follow:

$$\begin{aligned}\text{Log}\, AE = \; & .223 * (Number\ of\ admissions) + \; .409 \\ & * (Number\ of\ patients) + .137 * (Age) + .387 * (Sex \\ & = female) + .116 \\ & * (Admission\ type = casualty\ and\ accidental\ emergency)\end{aligned} \tag{4.5}$$

Therefore, the final index is formulated as follow:

$$\begin{aligned}AE = \; & 1.671^{(Number\ \ of\ admissions\ )} * 2.564^{(Number\ \ of\ patients\ )} * 1.370^{(Age)} \\ & * 2.437^{(Sex\ = female\ )} * 1.306^{(Admission\ \ type\ = casualty\ \ and\ \ accidental\ \ emergency\ )}\end{aligned} \tag{4.6}$$

This composite index (Formula 4.6) then can be used on any relational or prediction models based on the future records of the employed dataset. The proposed index is then expected to improve the accuracy of prospective relational and prediction models as well. It should be noted that it would not be prudent to generalize this index for any other hospital episode datasets since it was only evaluated on the employed dataset in this thesis.

4.7 Discussion and Conclusion

To examine the association of HWIs with AEs, three measurements of HWIs (peak, median and first day) were operationalized in this thesis by using daily values of HWIs. These measurements were then employed in separate adjusted models. The separation of

measurements was essential to avoid the inter-correlation effects between different measurements of HWIs for an identical HWI. Furthermore, to achieve a reliable adjusted model, a comprehensive suite of HWIs including volume, throughput, nurse patient complexity, and nurse staffing was employed. A reliable adjusted model is a model that seeks to minimize the overestimation or underestimation of the effect of a HWI on AEs (omitted variable bias effect) by inclusion of sufficient numbers of HWIs within adequate dimensions. Moreover, it should reach a desirable amount of accuracy.

Four significant findings were identified in this thesis. Firstly, the peak measurements of HWIs had the most effect on an increased likelihood of a patient's AE. For instance, using the peak measurement of HWIs (versus the median measurement of HWIs) demonstrated that higher numbers of HWIs (such as number of patients, number of medical admissions) were associated with an increased likelihood of a patient's AE. Secondly, the association of HWIs with AEs varied significantly based on patient type. For example, it was found that medical patients were more likely to face an AE when they were exposed to intensified HWIs compared to surgical patients. Thirdly, there could be a hidden association between HWIs and AEs. For example, results showed that while the higher percentage of emergency admission (using peak measurement) was associated with an increased likelihood of a patient's CHADx 9 AE (Genitourinary AEs), there were no association between higher percentage of emergency admission and increased likelihood of all types of AEs (all CHADx categories). Lastly, this thesis' result highlighted the effects of higher bed occupancy on increased likelihood of a patient's AE in comparison to other HWIs employed in this thesis. This was achieved by using a fully adjusted model which mitigated the overestimation effect due to the lack of employing the full aspects of HWIs.

These findings can be categorized further in several aspects. Firstly, when comparing the results of the association of peak of daily HWIs values with median or first day measurement of HWIs values, higher numbers of HWIs (when utilized as peak measurement of HWIs) showed a significant association with an increased likelihood of a patient's AE. The higher numbers of HWIs, as utilized by peak measurement, were observed in both medical and surgical samples. For example, in the medical sample, and by utilizing the first day measurement, no HWI was significantly associated with an increased likelihood of a patient's AE. In addition, utilizing the median measurement, only higher numbers of patients (bed

occupancy) was associated with an increased likelihood of a patient's AE. However, utilizing the HWIs by peak measurement, the number of patients and number of medical admissions were associated with an increased likelihood of a patient's AE (Figure 4.1). Moreover, in surgical patients, no HWI by utilizing either median or first day measurement was associated with an increased likelihood of a patient's AE. However, once again, utilizing the peak measurement, the number of patients was associated with an increased likelihood of a patient's AE (Figure 4.2).

The higher frequency of significant associations of HWIs by utilizing peak measurements was evident with the conducted subgroup analysis of AEs in CHADx 5 and CHADx 9 AEs. Only the model which utilized the peak measurement of HWIs showed a significant association of HWIs with an increased likelihood of a CHADx 5 and CHADx 9 AEs (refer to Section 4.5: Subgroup Analysis of AEs)[77].

The above findings on the substantial effect of peak measurement of HWIs (in the term of higher numbers of HWIs which have significant effect on the increased likelihood of a patient's AE) in comparison to other measurements (median or first day measurement) are similar to the findings of Tarnow-Mordi et al. (2000). These authors found a similar trend between ICU occupancy (as a volume dimension of HWIs) and patient in-hospital mortality. Tarnow-Mordi et al. (2000) found stronger associations (higher β coefficients) between ICU occupancy and in-hospital mortality when it was measured by peak in comparison to average or first day measurement.

Secondly, it was concluded that the effect of HWIs on AEs was more evident in medical patients compared to surgical patients (Figures 4.1 and 4.2). In other words, in medical patients versus surgical patients, (regardless of the measurement of HWIs), more HWIs were observed in which intensified values had a significant association with an increased likelihood of a patient's AE. For example, when utilizing the HWIs by median values within the medical sample, only the number of medical admissions had a significant association with an increased likelihood of a patient's AE (Figure 4.1). This was in direct contrast to the surgical sample (using median measurement), where no indicator was observed to have this association with an increased likelihood of a patient's AE (Figure 4.2). Moreover, when

[77] The significant associations were for higher number of patients with an increased likelihood of a CHADx 5 AE and higher percentage of emergency admissions with an increased likelihood of a CHADx 9 AE (Table 4.7).

utilizing the HWIs by peak values within the medical sample, higher values of 'number of medical admissions', and 'number of patients' were associated with an increased likelihood of a patient's AE (Figure 4.1). In contrast, in the surgical sample, only the higher values of the 'number of patients' were associated with an increased likelihood of a patient's AE (Figure 4.2). This may indicate that the effect of intensified HWIs on AEs is more evident in less severe medical patients (compared to more severe surgical patients)[78]. In other words, when hospitals face an intensified workload, they may compromise the effectiveness of care for less severe patients to provide more effective care for more severe patients.

The above finding on the higher effect of intensified hospital workload on increased likelihood of patient adverse outcomes (as demonstrated by AEs) in medical patients concurs with the findings of Schwierz et al. (2012). They indicated that when HWIs (the unexpected demand or throughput dimension of HWIs) are intensified, medical patients are more likely to face adverse outcomes such as mortality and re-admission rate.

Additionally, results indicated a significant association of higher values of some of HWIs with a particular type of AE (CHADx category), while this association was not observed with all types of AEs. For example, while the percentage of emergency admissions was associated with an increased likelihood of a patient's CHADx 9 AE (Table 4.7), this association was not observed with all types of AEs (Table 4.4). These findings are similar to the findings of Tibby et al. (2004) and Duffield et al. (2011) who found a significant association of higher HWIs (particularly bed occupancy) with an increased likelihood of a patient's particular type of AE or medication error. The association of higher HWIs with an increased likelihood of particular type of AEs can infer a covert association between HWIs and AEs, as it could be significant for a particular type but not be significant for all types of AEs.

Another observation was the significant influence of unobserved or unmeasurable effects on the association of HWIs with AEs. These effects (that could not be employed in the conceptual framework), are due to heterogeneity among patients and are known as random effects. In particular, the random effect of HWIs on AEs was examined within patients with different adjacent DRGs. The random effect was observed on the association of medical

[78] As described earlier in Chapter 3 (Section 3.8.3: Stratified analysis), surgical patients are expected to have higher DRG cost weights thus needing more hospital resources for treatment. This was confirmed based on the employed episode dataset in this thesis (Table 4.1).

admissions with the likelihood a patient's AE by utilizing median or peak measurement of HWIs (refer to Section 4.4: Patient exposure to HWIs and AEs). The significant influence of random effects of HWIs on AEs demonstrated the association of HWIs with AEs could vary based on different characteristics of patients. These different characteristics were not employed in the conceptual model and are deemed to be due to unobservable and immeasurable effects. It is notable that, to the knowledge of the researcher, no study in the literature has examined the random effect of HWIs on AEs.

From the conducted analyses, it was found that the hospital bed occupancy (or equivalently hospital number of patients) was the most frequent HWI affecting the likelihood of a patient's AE. Bed occupancy was found to have the most effect as it was observed three times in the association of HWIs with AEs using three different analyses (bed occupancy using median measurement in medical samples – Figure 4.1, bed occupancy using peak measurement in both medical and surgical samples – Figures 4.1 and 4.2). Therefore, it can be concluded that among HWIs, bed occupancy or the volume dimension of HWIs has a more substantial effect on the increased likelihood of a patient's AEs in comparison to other HWIs in other dimensions.

The subgroup analysis of AEs revealed different types of AEs (identified by CHADx categories) could either increase or decrease the likelihood of each other. This was obtained for the subgroup analysis of AEs conducted in this thesis on CHADx 9 and CHADx 5 AEs (Table 4.8). Therefore, the occurrences of different types of AEs could increase the likelihood of other types of AEs, for example, by increasing the likelihood of medication errors that are related to the AEs. On the other hand, they could decrease the likelihood of other types of AEs as well. This relationship is complex and it depends on the type of AE being examined. More discussion on the association of different types of AEs with each other is beyond the scope of this thesis and warrants a separate study. It is notable that the results obtained in this thesis that suggest different types of AEs (identified by CHADx major categories) could affect the occurrence of others, is innovative in the literature.

Lastly but possibly most importantly, in terms of methodology and design, the innovation of this study is the incorporation of the effect of all HWIs (in four broad dimensions) on AEs in

addition to other unobservable effects (random effects)[79]. These unobservable effects cannot be employed by any conceptual model. Utilization of HWIs by comprehensive dimensions along with consideration of their random effect results in a reliable adjusted model. This reliable adjusted model establishes a true and unbiased association between HWIs and AEs.

[79] As described in the Chapter 2 (Section: 2.3.1.3: Wards), the unobservable effects are any immeasurable effect or any other effect that cannot explicitly be employed in the conceptual model. For example, there is no definite metric to measure patients' characteristics such as mood or perception, or hospital characteristics such as hospital internal policies. Thus they cannot be employed in the conceptual model and are examples of random effects.

Chapter 5: Conclusion

5.1 Introduction

This chapter summarizes the strengths, significance and novelty of this thesis. The shortcomings of this thesis due to methodological and implementation limitations are presented. Suggestions for overcoming these issues, and recommendations for future research work are also provided.

5.2 Strengths, significance and innovation

This thesis set out with the aim of examining the association of HWIs with AEs. A hospital episode dataset is the source of the thesis' data. The use of hospital admission data as a measure of outcome has been used in most previous clinical studies, but this thesis has developed a new application for such data to support hospital operational management in a way that is potentially informative about the burden to health services associated with workload. Further research based on this source of data is both time and cost-effective and involves lower risk for research participants, namely patients (Dunn et al., 2015). This thesis shows hospitals and health systems may benefit from the better use of a hospital episode dataset for operational management. According to Heslop (2014), the use of casemix or hospital activity data has many benefits to health service organisations including that access is feasible and affordable, that the data provide a comprehensive retrospective review of patient care activity and that it is being considered for national outcome data monitoring and reporting. It paves the way for a move towards analytic discoveries from such data in a manner that can support health service organizations to gain insight into patient information and what managers can do for their patients.

This thesis employed a comprehensive suite of HWIs with a number of dimensions (refer to Section 3.2: Conceptual Framework). Although previous studies have noted significant effects of HWIs on the increased likelihood of AEs (Duffield et al., 2011; Weissman et al., 2007), there is a significant gap in current literature because the majority of these studies have failed to use a comprehensive suite of HWIs in an adjusted model. This implies that the reported associations on the significant effects of higher values of HWIs with increased likelihood of patient adverse outcomes could be inaccurate and misleading. In contrast, this thesis adapted the suggested framework of HWIs by Weissman et al. (2007) using four broad dimensions, namely volume, throughput, patient complexity, and nurse staffing (refer to Section 3.2:

Conceptual Framework). The utilization of all these dimensions of HWIs alongside a comprehensive suite of HWIs for each dimension obtained from the episode dataset, and the subsequent analysis in an adjusted model, has reduced bias both within and between key variables by factoring in the overall effects of HWIs on AEs. The adjusted model ascertained relationships between all inter-correlated (dependent) input and controlling indicators toward the output variable AEs. To some extent these variables are inter-correlated, for example emergency admissions could be correlated with the number of medical or surgical admissions. This adjustment in the analytical process has reduced potential for the overestimation or underestimation of the effect of the HWI on AEs.

This thesis examined the association of HWIs with AEs at the patient level (refer to Chapter3, Section 3.2: Conceptual Framework). This association was obtained by examining the association of patient exposure to HWIs with the likelihood of a patient's AE. It should be noted that an adjusted model at patient level has a higher reliability and accuracy in comparison to an adjusted model at higher hospital hierarchical levels such as hospital or ward level. This is because a model at patient level explicitly includes the effect of patient characteristic indicators. In contrast, models at hospital or ward level that use aggregated rates of AEs (using the individual patient rate of AEs), need a complex risk adjustment process to include the effect of individual patient characteristics in their adjusted models. This is a necessary step to achieve a reliable adjusted model to truly represent the association of HWIs with AEs.

It should be taken into consideration that the association between HWIs and the likelihood of a patient's AE could vary based on the heterogeneous patients' characteristic indicators known as random effects (refer to Chapter 2, Section 2.3.1.3: Ward). These heterogeneous characteristic indicators usually occur among groups of patients with identical characteristics such as DRGs (Berry Jaeker & Tucker, 2012a). Random effects of HWIs on AEs are usually unobservable effects related to patient heterogeneous characteristics. Since these effects are unobservable, they cannot be explicitly defined and included in the conceptual model. The random effects could have an additional and substantial impact on the significances of the associations between HWIs and AEs. Therefore, to obtain a fully adjusted model of HWIs

with AEs, apart from fixed effects of HWIs, the random effects of HWIs on AEs were included in the adjusted models of this thesis[80].

It is notable that by considering hospital or hospital wards as the context of the study, there have only been two studies (Evans & Kim, 2006; Weissman et al., 2007) on the association between patient exposure to HWIs and the likelihood of a patient's AE. However, both these studies had significant drawbacks such as using an unadjusted model on the association of HWIs with AEs (Weissman et al., 2007) and employing FTR as the only measurement of AEs (Evans & Kim, 2006). While Weissman et al. (2007) employed a comprehensive dimension of HWIs in the conceptual model, in the implementation phase they used separate models for each HWI. However, this could lead to a spurious and overestimated association between the employed HWI and AEs due to the omitted variable bias effect of neglected HWIs (refer to Section 2.3.1.1: ICU).

Furthermore, this thesis utilized CHADx, an automated reporting tool, to identify and categorize prospective AEs from hospital-acquired complications. CHADx is often used to collect data on patients with hospital-acquired complications to increase emphasis on patient safety and quality of care. To identify AEs, either of the two following assumptions needed to be met (refer to Chapter 3Section 3.4: Identification of AEs from CHADx);

1. The hospital-acquired complication (CHADx complications) should be due to a hospital-related external cause code, or
2. The hospital-acquired complication should genuinely represent an AE.

To the knowledge of the researcher, no previous study has utilized CHADx to capture AEs from hospital-acquired complications. Thus, this thesis is the first study to examine the association of HWIs with AEs using the CHADx tool.

The utilization of CHADx to capture and categorize different types of AEs enabled this thesis to conduct a subgroup analysis of AEs in order to examine the association of HWIs with a particular type of AE. The subgroup analysis of AEs in this thesis was conducted based on CHADx 5 and CHADx 9 AEs. This is because in these categories, the adjusted models reached a desirable level of accuracy (refer to Chapter 4, Section 4.5: Subgroup Analysis of

[80] The effect of random effects on AEs was insignificant in my analysis. Even though, the effect was not considered in my analysis if it was insignificant. This omission was expected to increase the accuracy of the adjusted model further.

AEs). The obtained result on the significant association of higher HWIs with increased likelihood of a particular type of AE could further indicate the covert association between HWIs and AEs, if the association was significant for a particular type of AE (CHADx category) but not for all types of AEs. This trend was observed for CHADx 9 AEs (refer to Chapter 4, Section 4.5: Subgroup Analysis of AEs, Table 4.7). Moreover, according to the result of subgroup analysis of AEs, the effect of different types of AEs on each other was obtained. To the knowledge of the researcher, no previous study has examined the association of occurrences of different types of AEs with each other. My findings may suggest the limited usage of CHADx to be conducted for subgroup analysis of AEs, this does not apply to the analyses conducted on all CHADx categories.

Additionally, apart from a reliable adjusted model (relational model), this thesis constructed a composite index (prediction model[81]) to predict the likelihood of a patient's AE. The composite index predicted the likelihood of a patient's AE based on patient exposure to HWIs on the day of admission and selected patient characteristics that were obtainable on the patient's admission date (refer to Chapter 3, Section 3.8.5: Composite index of patient exposure to HWIs). This index was originally constructed based on an exhaustive search on employed indicators using a base logistic regression classifier. The index was then validated by 2-fold cross validation based on evaluating adjusted models which employed the training index. The results were promising and showed the improvement of accuracy of the adjusted model (for example, in term of overall accuracy or percentage of correctly classified samples) when using the constructed index. Hence, this index can be used in any adjusted model to examine the association of HWIs with the likelihood of a patient's AE. It should be noted that building such a composite index was also novel in the literature; no previous study has established a composite index of patient exposure to HWIs based on the likelihood of a patient' AE.

5.3 Limitations

Several limitations in this study are acknowledged. Firstly, this study is a single-centre study conducted within one hospital; therefore, specific hospital characteristics could be a structural variable that limits the ability to generalise the findings. Secondly, the existing dataset did not

[81] An adjusted model refers to a relational model that examines the association between independent indicators with a dependent indicator based on an existing training dataset. In contrast, a prediction model provides a trained model (based on the training set) which can be used for the prediction of a dependent indicator for future and unforeseen data.

include the onset flag indicator to differentiate comorbid conditions from hospital-acquired complications. Therefore, it could be possible that some hospital-acquired complications are captured as comorbid conditions. Thirdly, nursing DRG cost weights were employed as a proxy measurement to obtain nurse staffing as a workload dimension of HWIs. Higher patients' nursing DRG cost weights indicate higher need for patients' clinical services which consequently requires higher nurse staffing (such as nurse to patient ratio); however, as a proxy measure, this may not represent the real values of nurse staffing in a hospital. Fourthly, the dataset was collected in 2001. While this may seem outdated, West et al. (2014) employed episode datasets related to the year 1998 for the association of HWIs with AEs, suggesting the findings are still relevant. Still, current datasets, though having refinements, are largely similar in health service organisations; however, using an old dataset may overlook the refinements that have been made to the data sets over time, even if workload indicators remain more or less the same. For instance, new DRGs may have been overlooked. Also since, 2016, greater enhancements have been made to flagging hospital acquired conditions in the data sets so the use of a 2016 data set could replicate this study more readily as the AEs are highly structured. It should be noted that hospital data sets are subject to ongoing refinement . Lastly, the measurement of exposure to bed occupancy was utilized by the numbers of patients during the patient hospitalization and it was assumed the number of beds is a constant parameter. Obviously, the number of hospital beds could change due to the hospital policies or circumstances to increase or decrease the number of beds in different departments. Therefore, the measurement of bed occupancy in this thesis may not represent its true value.

5.4 Suggestions for Future Research Work

There are some possible suggestions for future research work. This study was conducted within a single centre (one hospital) using a small dataset. Future work should employ a larger dataset and there is potential to incorporate data across multiple hospitals. This would result in higher applicability and generalisation of the findings. Additionally, a dataset with an onset flag indicator could be used to avoid the inaccuracy of differentiations of hospital-acquired complications from comorbid conditions.

As this thesis has mainly focused on hospital acquired complications for the detection of AEs, future research can investigate additional algorithms and methods to detect AEs based on other sources of patient adverse outcomes such as medication errors, death and prolonged length of stay. Further research can be undertaken to investigate the effects of these adverse

outcomes on AEs by doing a sensitivity analysis. Future research could also use the conceptual framework I have developed for further testing of its relevance in clinical practice.

Another important consideration for future research is the hierarchical level of exposure to workload levels. The employed concept of patient exposure to HWIs in this thesis was measured at patient level, though it captured exposure of patients to workload variables that are measured at the hospital level (for example, patient exposure to hospital bed occupancy). The exposure of patients to workload could be further analysed at unit levels instead, such as hospital wards or units (for example, patient exposure to unit bed occupancy instead of exposure to hospital bed occupancy). It has been suggested that the effect of patient exposure to HWIs on patient adverse outcomes could be more evident when the exposure is measured at the lower hospital hierarchical levels (Duffield et al., 2011). Measuring the patient exposure to HWIs at the ward or unit level was impossible to accomplish in this thesis, as the employed episode dataset did not include any indicator representing hospital units. Future research could examine the effect of patient exposure to HWIs at lower hospital hierarchical levels (for example hospital units versus the hospital itself) on the increased likelihood of a patient's AE.

5.4.1 Further methodological development

The adjusted and prediction models (composite index) in this study were constructed predominantly by binary logistic regression. Other non-linear and machine learning classifiers such as decision trees (Quinlan, 1987), bayesian networks (Pearl, 1988), nearest neighbour classifiers (Altman, 1992), and neural networks (McCulloch & Pitts, 1943) could be employed. These classifiers may offer even higher accuracies than the base binary logistic classifier that was employed in the adjusted models of this thesis. The implementation of random effects in non-linear machine learning classifiers is primitive in the literature and needs further research and development.

Moreover, this thesis employed an exhaustive search for construction of a composite index. This was based on analyses performed on the current episode dataset, which showed a promising result. Other search strategies such as best first search (Pearl, 1984), genetic search (Mitchell, 1998), and ranker search methods such as gain ratio (Quinlan, 1986), which are even more efficient (have less time complexity) than an exhaustive search, could be employed instead. These search strategies could lead to more efficient predictive models (in term of

classification accuracy) when an evaluation method such as k-fold cross validation is employed.

5.5 Conclusion

This thesis developed both relational (adjusted model) and prediction models (composite index) for examining the association between patient exposure to HWIs and the likelihood of a patient's AE. In the relational model (adjusted model), this thesis described how the association of patient exposure to HWIs could increase the likelihood of a patient's AE. Moreover, a prediction model was developed based on patient exposure to HWIs on the admission day. This model was trained using an exhaustive search to select a set of optimized HWIs (a composite index) on the admission date, which achieved higher accuracy for the prediction of the likelihood of a patient's AE. It was suggested the current approach (using exhaustive search) is a promising way to build an accurate prediction model. Consequently, a composite index (Chapter 4, Formula 4.6) using the entire records in the employed dataset in this thesis was established. This index is expected to increase the accuracy of any prospective adjusted or prediction model based on future records of employed hospital episode dataset. It should be noted that the ability to generalise this index to any other dataset is not proven since it was only evaluated using the employed dataset in this thesis.

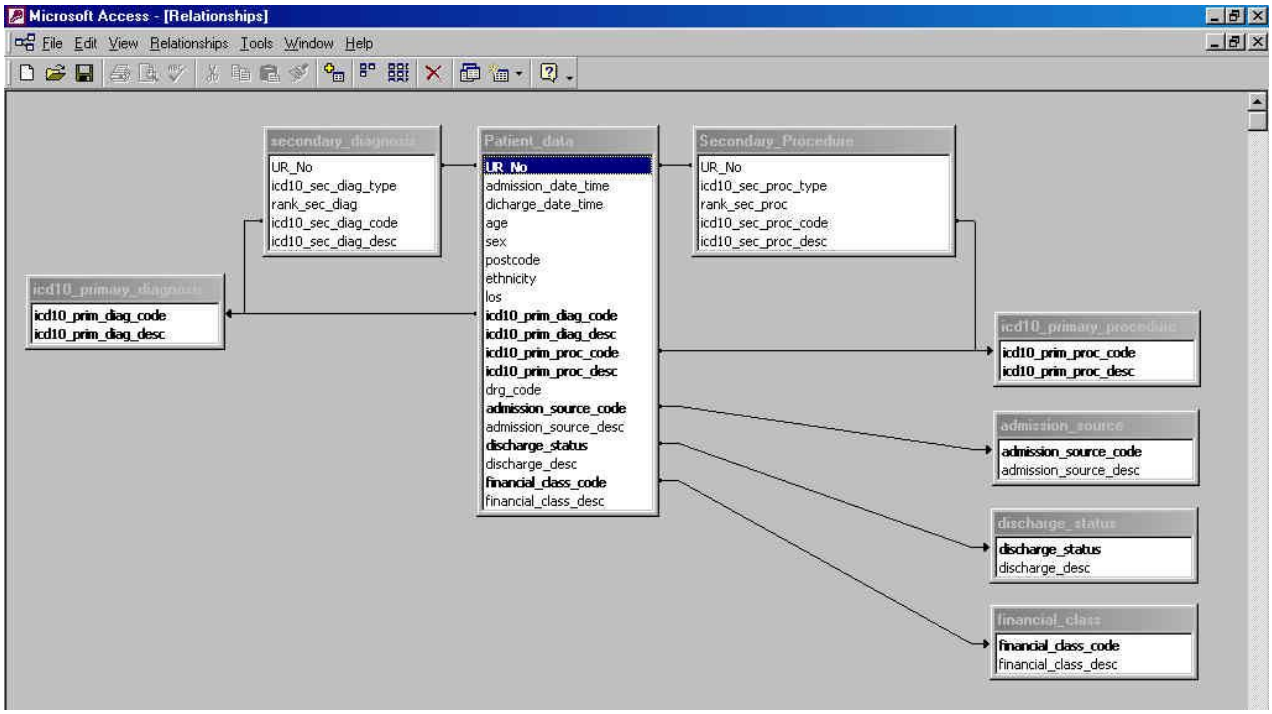
Hospital workload intensity has been the subject of much research as clinicians with additional workload pressures are subject to higher human errors leading to increased likelihood of patients' AEs. It should be noted that the employed adjusted model in this thesis highlighted the HWIs that have more substantial effect on the increased likelihood of a patient's AE. This could be relevant for hospital authorities. For example, based on the results obtained in this thesis, it was suggested that higher hospital bed occupancy in comparison to other HWIs such as number of admissions and discharges, hospital patient complexity and hospital requirement for higher nurse staffing has higher substantial effect on the increased likelihood of a patient's AE. Therefore, this study may assist hospital administrators to target resources to areas when care could be potentially jeopardised. Hospital decision makers may need to prioritise resources to increased department bed capacity situations during critical points of workload to decrease patients' AEs.

The composite measure of hospital workload intensity developed in this thesis may be valuable to policy and health service officials at many levels. The future outcome of a valid

and reliable workload intensity composite measure may help clinicians define suitable workload standards for hospital organisations. It could assist hospital organisational officials to monitor their hospital's workload intensity and possibly, capacity. Further, it may support health services researchers to standardize measures of workload intensity for benchmarking and aid in the examination of relationships between practice environment features (for example, job satisfaction ratings, turnover intentions and assessments of quality of care) and workload intensity, in a systematic and standardized way.

Appendices

Appendix A: Episode Dataset Structure



Appendix B: Charlson Comorbid Conditions and ICD-10 Codes[82]

Comorbidities	ICD-10 codes	Comorbidities	ICD-10 codes
Myocardial infarction	I21.x, I22.x, I25.2	Diabetes without chronic complication	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
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	Diabetes with chronic complication	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
Peripheral vascular disease	I70.x, I71.x, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9	Hemiplegia or paraplegia	G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0–G83.4, G83.9
Cerebrovascular disease	G45.x, G46.x, H34.0, I60.x–I69.x	Renal disease	I12.0, I13.1, N03.2–N03.7, N05.2–N05.7, N18.x, N19.x, N25.0, Z49.0–Z49.2, Z94.0, Z99.2
Dementia	F00.x–F03.x, F05.1, G30.x, G31.1	Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin	C00.x–C26.x, C30.x–C34.x, C37.x– C41.x, C43.x, C45.x–C58.x, C60.x– C76.x, C81.x–C85.x, C88.x, C90.x–C97.x

[82] The implementation of this index is based on Quan et al. (2005)'s study as employed in this thesis.

Chronic pulmonary disease	I27.8, I27.9, J40.x–J47.x, J60.x–J67.x, J68.4, J70.1, J70.3	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
Rheumatic disease	M05.x, M06.x, M31.5, M32.x–M34.x, M35.1, M35.3, M36.0	Metastatic solid tumor	C77.x–C80.x
Peptic ulcer disease	K25.x–K28.x	AIDS/HIV	B20.x–B22.x, B24.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		

Appendix C: Classification of Hospital-Acquired Diagnoses (CHADx)[83]

Major CHADx categories	Minor CHADx categories	Description	ICD-10 codes (Business rules)
MCHADx1, Post-Procedural Complications	1.1	Complications of infusion/transfusion	T80.1- T80.9
	1.2	Gas embolism	T80.0, T70.3, O88.0
	1.3	Failed or difficult intubation	T88.4
	1.4	Other haemorrhage and haematoma complicating procedure	T81.0
	1.5	Accidental puncture/laceration during procedure	T81.2
	1.6	Foreign body or substance left following procedure	T81.5- T81.6
	1.7	Other complications of surgical and medical care NEC (including shock)	T81.1, T81.7- T81.9, T88.0- T88.1, T88.8- T88.9
	1.8	Disruption of wound	T81.3, O90.0- O90.1
	1.9	Wound infection (excluding septicaemia)	T81.41, O86.0
	1.10	Complications of cardiac and vascular implants (excluding septicaemia)	T82
	1.11	Complications of genitourinary implants (excluding septicaemia)	T83
	1.12	Complications of orthopaedic implants (excluding septicaemia)	T84
	1.13	Complications of other implants (excluding septicaemia)	T85
	1.14	Complications of transplants	T86
	1.15	Complications of reattachment and amputations	T87
	1.16	Post-procedural disorders: endocrine and metabolic	E89

[83] The codes are based on CHADx version 5.0 (Australian Commission on Safety and Quality in Health Care (ACSQHC), 2013).

	1.17	Post-procedural disorders: nervous system	G97
	1.18	Post-procedural disorders: eye and ear	H59, H95
	1.19	Post-procedural disorders: circulatory system	I97
	1.20	Post-procedural disorders: respiratory system	J95
	1.21	Post-procedural disorders: digestive system	K91
	1.22	Post-procedural disorders: musculoskeletal system	M96
	1.23	Post-procedural disorders: genitourinary system	N99
MCHADx2, Adverse Drug Events	2.1	Skin Adverse effects due to systemic antibiotics	Y40, Y41+ L20- L30 (excluding L22.0- L23.2, L23.4- L24.3, L24.5- L25.0, L25.2- 25.9)& R20- 23 (excluding R22.0- R22.9)
	2.2	Other adverse effects due to systemic antibiotics	Y40, Y41
	2.3	Nausea & vomiting due to antineoplastic drugs	Y43.1- Y43.3+ R11
	2.4	Other adverse effects due to anti neoplastic drugs	Y43.1- Y43.3
	2.5	Coagulation defect due to drugs affecting blood constituents	Y44+ D68
	2.6	Other adverse effects due to drugs affecting blood constituents	Y44
	2.7	Nausea and vomiting due to opioids and related analgesics	Y45.0+ R11
	2.8	Alterations to mental state due to opioids and related analgesics	Y45.0+ F05.8, F05.9, R40.0- R40.2, R41.0- R41.8, orR44.0- R44.8
	2.9	Other adverse effects due to opioids and related analgesics	Y45.0
	2.10	Adverse effects due to anaesthesia (including misadventure)	Y48; Y60- 84+ T88.2, T88.3 or T88.5
	2.11	Hypotension due to anaesthesia	Y48+ I95
	2.12	Alterations to mental state due to anaesthesia	Y48+ F05.8, F059, R40.0- R40.2, R41.0- R41.8 or R44.0- R44.8
	2.13	Other adverse effects due to drugs affecting cardio vascular system	Y52
	2.14	Hypotension Delirium Tremens drugs affecting cardiovascular system	Y52+ I95.2
	2.15	Adverse effects due to insulin & oral hypoglycaemics	Y42.3

	2.16	Adverse effects due to other drugs	Y42 (excluding Y42.3), Y43.0, Y43.4- Y43.9, Y45 (excluding Y45.0), Y46- Y47, Y49- Y51, Y53- Y59, D52.1, D59.2.D61.1, E06.4, E16.0, E23.1, E24.2, E27.3, G21.1, G24.0, G25.1, G25.4, G44.4, G62.0, G72.0, I95.2, J70.4, L23.3, L24.4, L25.1, L27.0, L27.1, L43.2, L56.0, L56.1, M10.27, N14.0- N14.2
	2.17	Anaphylactic shock due to correct drug properly administered	T88.6; T78.2 followed by Y40- Y59
	2.18	Accidental overdose of drug or wrong drug given or taken in error	X40- X44
MCHADx3, Accidental Injuries	3.1	Falls with fractured femur	W01- W19 (excluding W02.0- W02.5, W09.0- W09.9, W11- W12, W14- 16)+ S72
	3.2	Falls with intracranial injury	W01- W19 (excluding W02.0- W02.5, W09.0- W09.9, W11- W12, W14- W16)+ W11- W12, W14- W16)+ S06.1- S06.9
	3.3	All other falls	W01.0, W01.1, W01.2, W03, W04, W05, W06, W07, W08, W10, W13, W17, W18, W19 (excluding W02.0- W02.5, W09.0- W09.9, W11- W12, W14- W16
	3.4	Injury due to assault	X85- Y09 (excluding X92.1- 2, Y03), Y35

	3.5	Other patient accidents (excluding poisoning)	W20- X59 (excluding W32- W34, W39, W59, X13.0, X20.0- X20.1)
MCHADx4, Specific Infections	4.1	Sepsis	A02.1, A32.7, A40, A41, A42.7, B37.7, T81.42, O75.3, O85, O88.3, P36, R65.0, R65.1, R57.2
	4.2	Mycoses	A31.8, A31.9, B35- B49 (excluding B37.7)
	4.3	MRSA	Z06.32
	4.4	Other drug resistant infections	Z06 (excluding Z06.32)
	4.5	Other infectious agents	A06.7, A28.0, A36.3, A36.8, A42.8, A42.9, A46, A48.0, A48.3, A49.0- A49.9, A86, A87.2, A87.9, B00.0- B00.9 (excluding B00.3, B00.4), B01.2, B01.9 (excluding B01.0, B01.1, B01.8), (excluding B02- B07), B08.4, B09, B15.9, B16.9, B17.1, B19.9, B25.0, B25.8, B25.9, B30.3, B30.9, B33.8, B34.8, B34.9, B60.8, B80, B83.9, B85.0, B85.2, B85.3, B85.4, B99
	5.1	AMI	I21- I22.9
	5.2	Pulmonary embolism (PE)	I26
	5.3	Cardiac arrhythmias, conduction disturbances & abnormal heartbeat	I44- I45, I47- I48, I49.1- I49.9, R00 (excluding with Y40- Y59)
	5.4	Ventricular fibrillation/cardiac arrest	I46, I49.0

MCHADx5, Cardiovascular Complications	5.5	Heart failure	I50
	5.6	Hypotension (not drug induced)	I95 (excluding with Y40- 59)
	5.7	Cerebro-vascular disease & TIA	I60- I67 (excluding I60.4, I60.6, I60.7, I65.2- I65.9, I66.0, I66.1, I66.3, I66.8, I66.9, I67.1- I67.5, I67.7- I67.9), G45, O87.3
	5.8	Venous thrombosis/embolism (not progressing to PE)	I80- I82, O22.3, O87.0- O87.1, O88.2
	5.9	Unstable and other angina	I20
	5.10	Cardiogenic and other shock	R57.0- R57.9
	5.11	Other circulatory system complications	I15.9, I23.0, I23.2, I23.3, I23.8, I24.0- I24.9, I27.2, I27.9, I28.8, I30.1- I30.9, I31.2, I31.3, I31.9, I33.0, I33.9, I34.8, I35.8, I36.1, I36.9, I37.1, I38, I40.8, I51.3, I51.4, I51.6, I51.8, I71.00, I71.01, I71.1, I72.0, I72.1, I72.2, I72.4, I72.8, I72.9, I74.0- I74.9, I77.0, I77.1, I77.2, I77.6, I77.8, I77.9, I78.8, I87.1, I87.8, I87.9, I88.0, I88.9, I89.0, I89.1, I89.8, I89.9, I99, R09.88
MCHADx6, Respiratory Complications	6.1	ARDS, respiratory failure & pulmonary collapse (including atelectasis)	J80, J96.0, J96.9, J98.1
	6.2	Aspiration pneumonia	J69
	6.3	Acute lower respiratory infections (including influenza & pneumonia)	J10- J18, J20- 22

	6.4	Pulmonary oedema, pneumothorax & pleural effusion	J90, J93, J94.0, J94.2
	6.5	Haemorrhage from respiratory passages	R04
	6.6	Asphyxia & respiratory arrest	R09.0, R09.2
	6.7	Breathing difficulties	R06.0- R06.5, R06.8, R09.1
	6.8	Other hospital-acquired respiratory disorders	J00, J01.0, J01.4, J01.9, J02.8, J02.9, J03.9, J04.0, J04.1, J05.0, J05.1, J06.9, J30.1, J30.3, J30.4, J34.0, J34.8, J38.00-J38.04, J38.3- J38.7, J39.0, J39.2, J39.3, J39.8, J40, J82, J84.9, J85.0- J85.3, J86.0, J86.9, J94.8, J98.0, J98.4- J98.9, R09.89
	7.1	Gastroenteritis	A02 - A09 (excluding A021, A04.7, A061- A06.6), K52
	7.2	Paralytic ileus & intestinal obstruction (w/o hernia)[84]	K56
	7.3	Enterocolitis Delirium Tremens Clostridium difficile	A04.7
	7.4	Constipation	K59.0 (excluding with drug effects Y40-59)
	7.5	Nausea and vomiting	R11
	7.6	GI bleeding not classified to a disease	K92.0- K92.2

[84] Excludes after T code.

MCHADx7, Gastrointestinal Complications	7.7	Other digestive system disorders	K05.0, K05.2, K05.5, K05.6, K06.2, K06.8, K06.9, K08.1, K08.81, K08.9, K10.2, K10.3, K10.8, K11.2, K11.3, K11.4, K11.7, K11.8, K12.0- K12.2, K13.0, K13.1, K13.7, K14.0, K14.6, K14.8, K20, K22.1, K22.2, K22.3, K22.6, K22.8, K22.9, K30, K31.0, K31.5, K31.6, K31.88, K31.9, K35.2- K35.8, K36, K37, K38.8, K55.0, K55.8, K55.9, K59.1, K59.4, K59.8, K59.9, K60.0, K60.2- K60.4, K61.0- K61.3, K62.4- K62.9, K63.0- K63.9, K65.0, K65.8, K65.9, K66.1, K66.8, K72.0, K72.9, K75.0, K75.8, K75.9, K76.3, K76.6- K76.9, K81.0, K81.8, K81.9, K82.2, K82.8, K82.9, K83.0- K83.4, K83.8, K83.9, K85.0- K85.9, K86.2- K86.9, K87.1, K90.3, K90.4, K90.9, K92.8, K92.9, R19.4, R19.5, R19.8
Dx8, Skin Condition	8.1	Pressure ulcers	L89
	8.2	Cellulitis[85]	L03

[85] Excludes after T code.

	8.3	Dermatitis, rash & other skin effects	L20- L30& R20- R23 (excluding with Y40- Y59 or Delirium Tremens (DT) drugs)
	8.4	Other skin disorders	L01.0, L01.1, L02.0- L02.9, L04.0- L04.3, L05.0, L05.9, L08.0, L08.8, L08.9, L10.9, L11.1, L13.8, L42, L43.9, L50.0, L50.8, L50.9, L51.1, L51.8, L51.9, L52, L53.0, L53.8, L53.9, L58.0, L58.9, L59.0, L59.8, L59.9, L60.0, L60.1, L60.3, L60.8, L60.9, L65.9, L70.0, L70.8, L70.9, L71.0, L71.9, L72.0, L72.1, L72.8, L72.9, L73.8, L73.9, L74.0, L74.1, L74.3, L88, L92.8, L92.9, L97, L98.0- L98.2, L98.5, L98.8, L98.9
MCHADx9, Genitourinary Complications	9.1	Acute & unspecified renal failure (excluding post procedural)	N17, N19
	9.2	UTIs	N10, N30.0, N39.0
	9.3	Urinary retention	R33
	9.4	Other complications & symptoms of the urinary system	N00- N39 (excluding N02 N03, N10, N17- N19, N20.0- N21.0, N30- N30.2), R30- R39 (excluding R33)

	9.5	Other complications of male & female genitals	N41.0, N41.9, N42.8, N45.0, N45.9, N48.1- N48.3, N48.5, N48.8, N48.9, N49.2, N49.9, N50.1, N50.8, N50.9, N51.1, N51.2, N51.8, N61, N64.1, N64.3- N64.8, N71.0, N71.9, N73.2, N73.5, N73.9, N76.0, N76.2, Nl76.4- N76.8, N82.0, N82.1, N82.3, N83.6- N83.9, N85.9, N88.8, N89.8, N89.9, N90.8, N90.9, N93.8, N93.9, N94.0, N94.4, N94.6, N98.1
MCHADx10, Hospital-acquired Psychiatric States	10.1	Depressive episode & symptoms involving emotional state	F32, R45 (excluding R45.6)
	10.2	Panic and other anxiety disorders	F41
	10.3	Adjustment & other psych disorders	F06.1, F06.33, F06.7- F06.9, F07.2, F07.8, F09, F23.30, F23.31, F23.90, F23.91, F29, F30.0, F30.2, F30.9, F38.8, F39, F40.8, F40.9, F43.0- F43.9, F44.5, F44.88, F44.9, F45.0, F45.31, F45.32, F45.34, F45.8, F45.9, F48.9, F51.0, F51.4, F51.5, F99, R45.6
	10.4	Alterations to mental state	F05.0- F05.9, R40.0- 40.2, R41.0- 41.8, R44.0- 44.8, R45.6

	10.5	Mental & behavioural disorders due to psychoactive substance use	F10.3, F10.4, F11.3, F11.4, F12.3, F12.4, F13.30, F13.31, F13.39, F13.40, F13.41, F13.49, F14.3, F14.4, F15.30, F15.31, F15.32, F15.39, F15.40, F15.41, F15.42, F15.49, F16.30, F16.31, F16.39, F16.40, F16.41, F16.49, F17.3, F17.4, F18.3, F18.4, F19.3, F19.4
	10.6	Patient self-harm (Including intentional and undetermined intent overdose)	X60- X84 (excluding X72- X75), Y10- Y34 (excluding Y22- Y25)
MCHADx11, Early Pregnancy Complications	11.1	Complications of abortion, ectopic and molar pregnancies	O03- O08 (excluding O05.0- O05.8)
MCHADx12, Labour, Delivery & Postpartum Complications	12.1	Foetal heart rate anomalies	O68.0, O68.2
	12.2	Foetal meconium and other distress	O68.1, O68.3- O68.9
	12.3	Complications of umbilical cord	O69
	12.4	Unsuccessful interventions during labour	O61, O66.5, O75.5- O75.6
	12.5	Complications of maternal anaesthesia during pregnancy and puerperium	O29, O74, O89
	12.6	First degree and unspecified perineal laceration	O70.0, O70.9
	12.7	Second degree perineal laceration	O70.1
	12.8	Third degree and fourth degree perineal laceration	O70.2- O70.3
	12.9	Maternal haemorrhage	O44.1, O46, O67, O72
	12.10	Other obstetric injury	O71, O90.2

	12.11	Other complications intra partum & postpartum	O75.0- O75.2, O75.4, O75.8- O75.9, O87.2, O87.8, O87.9, O90.3- O90.9, F53
	12.12	Retained placenta	O73
	12.13	Maternal infection (excluding wound infection & septicaemia)	O86.1- O86.8, O41.1
	12.14	Breast disorders associated with childbirth	O91- O92
	12.15	Other disorders predominantly related to pregnancy	O20.0, O20.8, O20.9, O21.0- O21.9, O22.2, O22.5, O22.8, O22.9, O23.0- O23.9, O25, O26.4, O26.5, O26.7, O26.81- O26.88, O26.9, O31.8, O41.8, O41.9, O42.0, O42.11, O42.12, O42.2, O42.9, O45.0, O45.8, O45.9, O47.1, O47.9, O88.1
MCHADx13, Perinatal Complications	13.1	Prenatal injuries	P03.2- P03.4, P96.50- P96.59
	13.2	Intracranial haemorrhage, hypoxia and other brain injuries	P10.0- P11.2, P20- P21, P52, P90- P91.9
	13.3	Other birth trauma	P11.3- P11.5
	13.4	Respiratory distress of new born	P22
	13.5	Aspiration & other respiratory disorders of new born86	P24- P26, P28 (excluding P28.81, P28.83)
	13.6	Circulatory disorders of new born	P29.0- P29.2, P29.4- P29.9, P29.3 (excluding P29.82)
	13.7	Perinatal infections (excluding septicaemia)	P37.5, P38, P39
	13.8	Haemorrhage and blood disorders of new born	P50- P51 & P53- P54
	13.9	Jaundice	P58- P59
	13.10	GI and feeding disorders of new born	P75- P78, P92, & R63.4

[86] Not including Snuffles and Grunting.

	13.11	Other neonatal complications	P60, P61.0- P61.9, P70.3- P70.9, P71.0- P71.9, P72.0- P72.9, P74.0, P74.1, P74.20- P74.29, P74.30- P74.39, P74.4- P74.9, P28.81, P28.83, P80.0, P80.8, P80.9, P81.0, P81.8, P81.9, P83.0- P83.9, P96.1, P96.2, P96.81, P96.89, P96.3
MCHADx14, Haematological Complications	14.1	Post haemorrhagic anaemia (not post-procedural)	D62
	14.2	Other hospital- acquired anaemia	D55.2, D59.3, D59.4, D59.6- D59.9, D61.9, D63, D64.1, D64.3, D64.8, D64.9
	14.3	Coagulation defects	D65, D68.3- D68.9 (excluding with Y40- Y59)
	14.4	Agranulocytosis, thrombocytopenia & other blood disorders	D69.0- D69.9, D70, D72.1- D72.9, D73.0, D73.1, D73.3, D73.5- D73.9, D75.1- D75.9, D80.1, D80.3, D84.8, D84.9, D89.0- D89.2, D89.8
MCHADx15, Metabolic Complications	15.1	Dehydration/volume depletion	E86 (excluding with Y40- Y59)
	15.2	Electrolyte disorders w/o dehydration	E87 (excluding with Y40- Y59 or w E86)
	15.3	Hospital-acquired nutrition deficiencies (including nutritional anaemia)	E40- E63 & D50- D53
	15.4	Hypo glycaemia & hyperglycaemia	E16.1- E16.2, R73
	15.5	Disorders of mineral metabolism	E83 (excluding with Y40- Y59)

	15.6	SIADH, hyperthyroidism & other metabolic disorders	E03.2, E05.4- E05.9, E06.0, E06.1, E06.9, E07.8, E07.9, E16.4, E20.9, E21.1- E21.4, E22.1, E22.2, E22.9, E23.3, E23.6, E26.9, E27.4, E27.8, E27.9, E29.1, E34.8, E34.9, E72.1, E73.8, E79.0, E80.1, E80.7
x16, Nervous System Complic	16.1	Hospital- acquired paralysis	G51.0, G81- G83
	16.2	Dystonia, tremors & gait disorders	G24.4- G24.9, G25.2- G25.9, R25- R27, R29.0, R29.2

	16.3	Other nervous system complications	G00.2- G00.9, G03.0, G03.9, G04.8, G04.9, G06.0- G06.2, G08, G21.8, G40.00, G40.10, G40.20, G40.21, G40.30, G40.50, G40.60, G40.70, G40.80, G40.90, G40.91, G41.8, G47.0, G47.1, G47.2, G50.8, G50.9, G52.1- G52.9, G54.0, G54.1, G54.4, G54.6, G54.7- G54.9, G55.1, G55.3, G56.1- G56.3, G56.8, G56.9, G57.0- G57.3, G57.8, G57.9, G58.0, G58.8, G58.9, G61.8, G62.8, G62.9, G63.8, G70.9, G72.8, G72.9, G73.6, G90.2, G90.8, G90.9, G91.3, G91.8, G91.9, G93.1, G93.2, G93.4, G93.5, G93.6, G93.8, G93.9, G95.0, G95.1, G95.2, G95.9, G96.0, G61.0, G96.9, G98, R29.5, R29.88
MCHADx17, Other Complications	17.1	Major symptoms	R02, R15, R16.1, R17, R19.0, R29.1, R47.0, R47.1, R48.1, R48.2, R49.1, R58, R68.0, R96.0
	17.2	Headache & migraine	R51, G43- G44
	17.3	Oedema & ascites	R18, R60
	17.4	Chest pain	R07.1- R07.4
	17.5	Abdominal pain	R10
	17.6	Fever (not classified to condition)	R50

	17.7	Convulsions	R56
	17.8	Dizziness, fainting & blackout	R42 & R55
	17.9	Complications of the eye and ear	H00- H95 (excluding H25)
	17.10	Musculoskeletal complications (not associated with falls)	M00.0- M99.9, R29.89
	17.11	Dysphagia	R13
	17.12	Other symptoms	R03.0, R03.1, R05, R06.6, 06.7, R07.0, R09.3, R12, R14, R19.6, R29.3, R43.1, R43.2, R43.8, R46.2, R46.4, R46.8, R47.8, R49.0, R49.2, R49.8, R52.0, R52.9, R53, R59.0, R59.1, R61.0, R61.1, R61.9, R63.0- R63.5, R63.8, R68.2, R68.8, R69

Appendix D: Australian refined diagnosis-related groups (AR-DRG) version 4.2[87]

MDC	DRG Code	DRG Description	DRG Type	DRG Cost Weight	Nursing DRG Cost Weight	MDC	DRG Code	DRG Description	DRG Type	DRG Cost Weight	Nursing DRG Cost Weight
Error DRGs	901Z	Extensive O.R. Procedure Unrelated to Principal Diagnosis	Surgical	3.97	4.05	MDC 08. Diseases and disorders of the musculo-skeletal system and connective tissue	I21Z	Local Excision and Removal Internal Fixation Devices of Hip and Femur	Surgical	1.20	1.02
	902Z	Non−Extensive O.R. Procedure Unrelated to Principal Diagnosis	Surgical	1.82	1.92		I22Z	Major Wrist Hand and Thumb Procedures	Surgical	1.14	0.56
	903Z	Prostatic O.R. Procedure Unrelated to Principal Diagnosis	Surgical	4.49	6.94		I23Z	Local Excision and Removal of Internal Fixation Device Excluding Hip and Femur	Surgical	0.69	0.33
	960Z	Ungroupable	Medical	1.09	0.86		I24Z	Arthroscopy	Surgical	0.69	0.28

[87] The information in this table was extracted from Australian Institute of Health and Welfare (AIHW, 2014b) and Independent Hospital Pricing Authority (IHPA, 2004) websites.

	961Z	Unacceptable Principal Diagnosis	Medical	0.46	0.46		I25Z	Bone and Joint Diagnostic Procedures including Biopsy	Surgical	2.22	2.48
	962Z	Unacceptable Obstetric Diagnosis Combination	Medical	1.24	2.87		I26Z	Other Wrist and Hand Procedures	Surgical	0.86	0.40
	963Z	Neonatal Diagnosis Not Consistent W[88] Age/Weight	Medical	2.53	3.07		I27Z	Soft Tissue Procedures	Surgical	1.22	0.97
Pre−MDC. Major procedures where the principal diagnosis may be associated	A01Z	Liver transplant	Surgical	30.23	13.79		I28A	Other Connective Tissue Procedures W CC[89]	Surgical	3.71	4.03
	A02Z	Multiple organs transplant	Surgical	16.50	8.95		I28B	Other Connective Tissue Procedures W/O[90] CC	Surgical	1.15	0.73
	A03Z	Lung transplant	Surgical	27.11	17.22		I60Z	Femoral Shaft Fractures	Medical	2.73	4.12

[88] W denotes with.
[89] CC denotes comorbidity and complications.
[90] W/O denotes without.

with any MDC	A04Z	Bone Marrow Transplant	Surgical	11.80	11.70		I61Z	Other Femoral Fractures	Medical	1.62	2.38
	A05Z	Heart transplant	Surgical	27.31	12.45		I62A	Fractures of Pelvis and Femoral Neck W Catastrophic CC	Medical	3.51	5.64
	A06Z	Tracheostomy Any Age Any Condition	Surgical	22.79	8.77		I62B	Fractures of Pelvis and Femoral Neck W Severe CC	Medical	2.05	3.17
	A40Z	ECMO W/O Cardiac Surgery	Surgical	35.78	7.21		I62C	Fractures of Pelvis and Femoral Neck W/O Catastrophic or Severe CC	Medical	0.99	1.28
	A41Z	Intubation Age<16	Surgical	5.08	3.40		I63Z	Sprains Strains and Dislocations of Hip Pelvis and Thigh.	Medical	0.76	0.79
MDC 01. Diseases and disorders of the nervous system	B01Z	Ventricular Shunt Revision W No Other O.R. Procedures	Surgical	2.58	2.29		I64A	Osteomyelitis (Age< 65 W Catastrophic or Severe CC) or Age>64	Medical	2.35	3.16

	B02A	Craniotomy W Catastrophic CC	Surgical	9.92	7.97		I64B	Osteomyelitis Age<65 W/O Catastrophic or Severe CC	Medical	1.07	1.42
	B02B	Craniotomy W Severe or Moderate CC	Surgical	5.69	4.40		I65A	Connective Tissue Malignancy including Pathological Fracture Age>64	Medical	1.39	2.07
	B02C	Craniotomy W/O CC	Surgical	4.26	2.94		I65B	Connective Tissue Malignancy including Pathological Fracture Age<65	Medical	1.15	1.51
	B03A	Spinal Procedures W Catastrophic or Severe CC	Surgical	599	5.92		I66A	Inflammatory Musculoskeletal Disorders (Age<65 W Catastrophic or Severe CC) or Age>64	Medical	1.75	2.13

	B03B	Spinal Procedures W/O Catastrophic or Severe CC	Surgical	3.24	2.34		I66B	Inflammatory Musculoskeletal Disorders Age<65 W/O Catastrophic or Severe CC	Medical	0.57	0.57
	B04A	Extracranial Vascular Procedures W Catastrophic or Severe CC	Surgical	4.00	3.21		I67A	Septic Arthritis W Catastrophic or Severe CC	Medical	2.96	4.17
	B04B	Extracranial Vascular Procedures W/O Catastrophic or Severe CC	Surgical	2.16	1.25		I67B	Septic Arthritis W/O Catastrophic or Severe CC	Medical	1.06	1.41
	B05Z	Carpal Tunnel Release	Surgical	0.55	0.21		I68A	Non−Surgical Neck and Back Cond W/O Pain Management Procedure/ Myelogram (Age<75 W CC) or Age>74	Medical	1.40	1.91

	B06A	Procedures for Cerebral Palsy Muscular Dystrophy Neuropathy W Catastrophic or Severe CC	Surgical	4.79	6.05		I68B	Non−surgical Neck and Back Cond W/O Pain Management Procedure/ Myelogram Age<75 W/O CC	Medical	0.61	0.66
	B06B	Procedures for Cerebral Palsy Muscular Dystrophy Neuropathy W/O Catastrophic or Severe CC	Surgical	1.12	0.64		I68C	Non−surgical Neck and Back Conditions W Pain Management Procedure/ Myelogram	Medical	0.52	0.38
	B07A	Peripheral and Cranial Nerve and Other Nervous System Procedures W CC	Surgical	3.14	3.10		I69A	Bone Diseases and Specific Arthropathies Age>74 W Catastrophic or Severe CC	Medical	2.41	3.86

	B07B	Peripheral and Cranial Nerve and Other Nervous System Procedures W/O CC	Surgical	1.12	0.56		I69B	Bone Diseases and Specific Arthropathies Age>74 W/O Catastrophic or Severe CC	Medical	0.86	1.23
	B40Z	Plasmapheresis W Neurological Disease	Other	1.52	1.47		I69C	Bone Diseases and Specific Arthropathies Age<75	Medical	0.62	0.69
	B41Z	Prolonged Monitoring for Complex Epilepsy	Other	1.45	2.39		I70Z	Non−Specific Arthropathies	Medical	0.89	1.06
	B60A	Non Acute Paraplegia/Quadriplegia W or W/O O.R. Procedures W Catastrophic CC	Medical	6.81	10.55		I71A	Musculotendinous Disorders Age>69 W CC	Medical	1.23	1.76

	B60B	Non Acute Paraplegia/ Quadriplegia W or W/O O.R. Procedures W/O Catastrophic CC	Medical	1.96	2.50		I71B	Musculotendinous Disorders (Age<70 W CC) or (Age>69 W/O CC)	Medical	0.67	0.81
	B61A	Spinal Cord Conditions W or W/O O.R. Procedures W Catastrophic or Severe CC	Medical	7.96	10.95		I71C	Musculotendinous Disorders Age <70 W/O CC	Medical	0.41	0.32
	B61B	Spinal Cord Conditions W or W/O O.R. Procedures W/O Catastrophic or Severe CC	Medical	2.26	2.47		I72A	Tendonitis Myositis and Bursitis (Age<80 W Catastrophic or Severe CC) or Age>79	Medical	1.57	2.25
	B62Z	Admit for Apheresis	Medical	0.30	0.29		I72B	Tendonitis Myositis and Bursitis Age<80 W/O Catastrophic or Severe CC	Medical	0.51	0.53

	B63Z	Dementia and Other Chronic Disturbances of Cerebral Function	Medical	2.60	4.98		I73A	Aftercare of Connective Tissue Disorders Age>59 W Catastrophic or Severe CC	Medical	2.64	4.16
	B64Z	Delirium	Medical	1.69	2.68		I73B	Aftercare of Connective Tissue Disorder (Age<60 W Catastrophic/ Severe CC) or (Age>59 W/O Catastrophic/ Severe CC)	Medical	0.99	1.26
	B65Z	Cerebral Palsy	Medical	1.09	0.61		I73C	Aftercare of Connective Tissue Disorders Age<60 W/O Catastrophic or Severe CC	Medical	0.47	0.39
	B66A	Nervous System Neoplasm Age>64	Medical	2.17	3.46		I74A	Injury to Forearm Wrist Hand or Foot Age>74 W CC	Medical	1.50	2.11

	B66B	Nervous System Neoplasm Age<65	Medical	140	1.82		I74B	Injury to Forearm Wrist Hand or Foot (Age<75 W CC) or (Age>74 W/O CC)	Medical	0.66	0.60
	B67A	Degenerative Nervous System Disorders W Catastrophic or Severe CC	Medical	3.26	4.93		I74C	Injury to Forearm Wrist Hand or Foot Age<75 W/O CC	Medical	0.47	0.30
	B67B	Degenerative Nervous System Disorders W/O Catastrophic or Severe CC	Medical	0.87	1.16		I75A	Injury to Shoulder Arm Elbow Knee Leg or Ankle Age>64 W CC	Medical	2.14	3.35
	B68A	Multiple Sclerosis and Cerebellar Ataxia W CC	Medical	2.53	3.82		I75B	Injury to Shoulder Arm Elbow Knee Leg Ankle (Age<65 W CC) or (Age>64 W/O CC)	Medical	0.93	1.21

	B68B	Multiple Sclerosis and Cerebellar Ataxia W/O CC	Medical	0.53	0.61		I75C	Injury to Shoulder Arm Elbow Knee Leg or Ankle Age<65 W/O CC	Medical	0.48	0.38
	B69A	TIA and Precerebral Occlusion W Catastrophic CC	Medical	2.21	3.42		I76A	Other Musculoskeletal Disorders Age>69 W CC	Medical	1.88	2.93
	B69B	TIA and Precerebral Occlusion W Severe CC	Medical	1.20	1.59		I76B	Other Musculoskeletal Disorders (Age<70 W CC) or (Age>69 W/O CC)	Medical	0.74	0.80
	B69C	TIA and Precerebral Occlusion W/O Catastrophic or Severe CC	Medical	0.68	0.75		I76C	Other Musculoskeletal Disorders Age<70 W/O CC	Medical	0.43	0.32
	B70A	Stroke W Severe or Complicating Diagnosis/ Procedure	Medical	4.12	6.40	MDC 09. Diseases and disorders of the skin,	J01Z	Microvascular Tissue Transfer for Skin Subcutaneous Tissue and Breast Disorder	Surgical	5.32	4.24

	B70B	Stroke W Other CC	Medical	2.17	3.13	subcutan-eous tissue and breast	J02A	Lower Limb W Skin Graft/Flap Repair W Ulcer/Cellulitis W Catastrophic CC	Surgical	9.35	12.66
	B70C	Stroke W/O Other CC	Medical	1.42	1.83		J02B	Lower Limb W Skin Graft/Flap Repair W Ulcer/Cellulitis W/O Catastrophic CC	Surgical	3.49	4.92
	B70D	Stroke Died or Transferred < 5 days	Medical	0.77	0.49		J03A	Lower Limb W Skin Graft/Flap Repair W/O Ulcer/Cellulitis W Catastrophic or Severe CC	Surgical	3.46	4.46
	B71A	Cranial and Peripheral Nerve Disorders W CC	Medical	1.91	2.62		J03B	Lower Limb W Skin Graft/Flap Repair W/O Ulcer/Cellulitis W/O Catastrophic or Severe CC	Surgical	1.38	1.53

	B71B	Cranial and Peripheral Nerve Disorders W/O CC	Medical	0.41	0.40		J04A	Lower Limb W/O Skin Graft/Flap Repair W Ulcer/Cellulitis W Catastrophic or Severe CC	Surgical	4.46	5.97
	B72Z	Nervous System Infection Except Viral Meningitis	Medical	2.26	2.67		J04B	Lower Limb W/O Skin Graft/Flap Repair W Ulcer/Cellulitis W/O Catastrophic or Severe CC	Surgical	1.70	2.03
	B73Z	Viral Meningitis	Medical	0.92	1.03		J05Z	Lower Limb W Other O.R. Procedure W/O Skin Graft/Flap Repair W/O Ulcer/Cellulitis	Surgical	1.30	0.98
	B74Z	Non-traumatic Stupor and Coma	Medical	0.82	0.86		J06A	Major Procedures for Malignant Breast Conditions	Surgical	1.78	1.37
	B75Z	Febrile Convulsions	Medical	0.42	0.48		J06B	Major Procedures for Non−Malignant	Surgical	1.39	0.84

								Breast Conditions			
	B76A	Seizure Age<3 or W Catastrophic or Severe CC	Medical	1.24	1.53		J07A	Minor Procedures for Malignant Breast Conditions	Surgical	0.85	0.41
	B76B	Seizure Age>2 W/O Catastrophic or Severe CC	Medical	0.54	0.52		J07B	Minor Procedures for Non−Malignant Breast Conditions	Surgical	0.59	0.20
	B77Z	Headache	Medical	0.43	0.35		J08A	Other Skin Graft and/or Debridement Procedures W Catastrophic or Severe CC	Surgical	2.98	3.05
	B78Z	Intracranial Injury	Medical	1.87	1.97		J08B	Other Skin Graft and/or Debridement Procedures W/O Catastrophic or Severe CC	Surgical	0.92	0.52
	B79Z	Skull Fractures	Medical	0.98	0.89		J09Z	Perianal and Pilonidal	Surgical	0.74	0.51

								Procedures			
	B80Z	Other Head Injury	Medical	0.40	0.26		J10Z	Skin Subcutaneous Tissue and Breast Plastic O.R. Procedures	Surgical	0.75	0.31
	B81A	Other Disorders of the Nervous System W Catastrophic or Severe CC	Medical	2.22	3.37		J11Z	Other Skin Subcutaneous Tissue and Breast Procedures	Surgical	0.44	0.21
	B81B	Other Disorders of the Nervous System W/O Catastrophic or Severe CC	Medical	0.83	0.94		J60A	Skin Ulcers Age>64	Medical	1.84	3.03
MDC 02. Diseases and disorders of the eye	C01Z	Procedures for Penetrating Eye Injury	Surgical	1.78	1.42		J60B	Skin Ulcers Age<65	Medical	1.32	1.81
	C02Z	Enucleations and Orbital Procedures	Surgical	1.52	1.22		J61Z	Severe Skin Disorders	Medical	0.73	0.95
	C03Z	Retinal Procedures	Surgical	1.06	0.68		J62A	Malignant Breast Disorders Age>69	Medical	1.18	1.69

								W CC			
	C04Z	Major Corneal Scleral and Conjunctival Procedures	Surgical	1.30	1.00		J62B	Malignant Breast Disorders (Age<70 W CC) or (Age>69 W/O CC)	Medical	0.75	0.92
	C05Z	Dacryocrysto-rhinostomy	Surgical	0.87	0.46		J62C	Malignant Breast Disorders Age<70 W/O CC	Medical	0.37	0.31
	C06Z	Complex Glaucoma Procedures	Surgical	0.82	0.73		J63Z	Non−Malignant Breast Disorders	Medical	0.49	0.39
	C07Z	Other Glaucoma Procedures	Surgical	0.86	0.44		J64A	Cellulitis Age>59 W Catastrophic or Severe CC	Medical	1.98	3.01
	C08Z	Major Lens Procedures	Surgical	0.80	0.17		J64B	Cellulitis (Age>59 W/O Catastrophic or Severe CC) or Age<60	Medical	0.86	1.09
	C09Z	Other Lens Procedures	Surgical	0.87	0.38		J65A	Trauma to the Skin Subcutaneous Tissue and Breast Age>69	Medical	0.92	1.24

	C10Z	Strabismus Procedures	Surgical	0.65	0.26		J65B	Trauma to the Skin Subcutaneous Tissue and Breast Age<70	Medical	0.41	0.27
	C11Z	Eyelid Procedures	Surgical	0.70	0.27		J66A	Moderate Skin Disorders W Catastrophic or Severe CC	Medical	1.62	2.36
	C12Z	Other Corneal Scleral and Conjunctival Procedures	Surgical	0.64	0.30		J66B	Moderate Skin Disorders W/O Catastrophic or Severe CC	Medical	0.65	0.81
	C13Z	Lacrimal Procedures	Surgical	0.43	0.21		J67A	Minor Skin Disorders W CC	Medical	1.20	1.67
	C14Z	Other Eye Procedures	Surgical	0.49	0.27		J67B	Minor Skin Disorders W/O CC	Medical	0.33	0.22
	C60A	Acute and Major Eye Infections Age>54	Medical	1.74	2.65	MDC 10. Endocrine, nutritional and metabolic diseases	K01Z	Diabetic Foot	Surgical	6.26	7.97
	C60B	Acute and Major Eye Infections Age<55	Medical	0.88	1.21		K02Z	Pituitary Procedures	Surgical	4.55	3.42

	C61Z	Neurological and Vascular Disorders of the Eye	Medical	0.64	0.65	and disorders	K03Z	Adrenal Procedures	Surgical	3.59	2.50
	C62Z	Hyphema and Medically Managed Trauma to the Eye	Medical	0.47	0.45		K04Z	Major Procedures for Obesity	Surgical	2.58	1.83
	C63A	Other Disorders of the Eye W CC	Medical	1.00	1.27		K05Z	Parathyroid Procedures	Surgical	1.95	1.40
	C63B	Other Disorders of the Eye W/O CC	Medical	0.39	0.33		K06Z	Thyroid Procedures	Surgical	1.73	1.01
MDC 03. Diseases and disorders of the ear, nose, mouth and throat	D01Z	Cochlear Implant	Surgical	7.80	0.75		K07Z	Obesity Procedures	Surgical	1.72	1.72
	D02A	Head and Neck Procedures W CC	Surgical	5.33	4.77		K08Z	Thyroglossal Procedures	Surgical	0.91	0.49
	D02B	Head and Neck Procedures W/O CC	Surgical	1.93	1.32		K09Z	Other Endocrine Nutritional and Metabolic O.R. Procedures	Surgical	4.09	4.15

	D03Z	Surgical Repair for Cleft Lip or Palate Diagnosis	Surgical	1.79	1.76		K40Z	Endoscopic or Investigative Procedure for Metabolic Disorders W/O CC	Other	0.55	0.39
	D04A	Maxillo Surgery W CC	Surgical	2.44	1.55		K60A	Diabetes W Catastrophic or Severe CC	Medical	1.89	2.54
	D04B	Maxillo Surgery W/O CC	Surgical	1.53	0.76		K60B	Diabetes W/O Catastrophic or Severe CC	Medical	0.87	1.00
	D05Z	Sialoadenectomy	Surgical	1.54	0.87		K61Z	Severe Nutritional Disturbance	Medical	3.44	5.49
	D06Z	Sinus Mastoid and Complex Middle Ear Procedures	Surgical	1.16	0.58		K62A	Miscellaneous Metabolic Disorders W Catastrophic CC	Medical	2.44	3.68
	D07Z	Salivary Gland Procedures Except Sialoadenectomy	Surgical	0.93	0.58		K62B	Miscellaneous Metabolic Disorders W Severe CC or (Age>74 W/O Severe CC)	Medical	1.09	1.49

	D08Z	Mouth Procedures	Surgical	0.77	0.40		K62C	Miscellaneous Metabolic Disorders W/O Catastrophic or Severe CC Age < 75	Medical	0.57	0.74
	D09Z	Miscellaneous Ear Nose Mouth and Throat Procedures	Surgical	0.86	0.44		K63Z	Inborn Errors of Metabolism	Medical	0.64	0.68
	D10Z	Rhinoplasty (W or W/O Turbinectomy)	Surgical	0.85	0.46		K64A	Endocrine Disorders W Catastrophic or Severe CC	Medical	2.12	2.81
	D11Z	Tonsillectomy or Adenoidectomy	Surgical	0.68	0.61		K64B	Endocrine Disorders W/O Catastrophic or Severe CC	Medical	0.73	0.65
	D12Z	Other Ear Nose Mouth and Throat Procedures	Surgical	1.08	0.72	MDC 11. Diseases and disorders of the	L01A	Kidney transplant w catastrophic or severe cc	Surgical	10.16	6.70
	D13Z	Myringotomy W Tube Insertion	Surgical	0.43	0.24		L01B	Kidney transplant w/o catastrophic or	Surgical	6.83	4.98

						kidney and urinary tract		severe cc			
	D40Z	Dental Extractions and Restorations	Other	0.58	0.23		L02Z	Operative Insertion of Peritoneal Catheter for Dialysis	Surgical	3.14	3.13
	D60A	Ear Nose Mouth and Throat Malignancy W Catastrophic or Severe CC	Medical	2.86	4.25		L03A	Kidney Ureter and Major Bladder Procedures for Neoplasm W Catastrophic or Severe CC	Surgical	6.21	5.78
	D60B	Ear Nose Mouth and Throat Malignancy W/O Catastrophic or Severe CC	Medical	0.95	1.01		L03B	Kidney Ureter and Major Bladder Procedures for Neoplasm W/O Catastrophic or Severe CC	Surgical	3.47	2.54
	D61Z	Disequilibrium	Medical	0.52	0.54		L04A	Kidney Ureter and Major Bladder Procedures for Non−Neoplasm W Catastrophic or	Surgical	4.36	4.56

								Severe CC			
	D62Z	Epistaxis	Medical	0.50	0.49		L04B	Kidney Ureter and Major Bladder Procedures for Non−Neoplasm W/O Catastrophic or Severe CC	Surgical	1.99	1.61
	D63A	Otitis Media and URI W CC	Medical	0.84	1.05		L05A	Transurethral Prostatectomy W Catastrophic or Severe CC	Surgical	3.55	4.84
	D63B	Otitis Media and URI W/O CC	Medical	0.47	0.54		L05B	Transurethral Prostatectomy W/O Catastrophic or Severe CC	Surgical	1.33	1.16
	D64Z	Laryngotracheitis and Epiglottitis	Medical	0.43	0.43		L06A	Minor Bladder Procedures W Catastrophic or Severe CC	Surgical	2.75	3.19
	D65Z	Nasal Trauma and Deformity	Medical	0.42	0.23		L06B	Minor Bladder Procedures W/O Catastrophic or	Surgical	0.94	0.77

								Severe CC			
	D66A	Other Ear Nose Mouth and Throat Diagnoses W CC	Medical	0.91	0.98		L07A	Transurethral Procedures Except Prostatectomy W Catastrophic or Severe CC	Surgical	1.97	2.13
	D66B	Other Ear Nose Mouth and Throat Diagnoses W/O CC	Medical	0.42	0.31		L07B	Transurethral Procedures Except Prostatectomy W/O Catastrophic or Severe CC	Surgical	0.73	0.38
	D67Z	Dental and Oral Disorders Except Extractions and Restorations	Medical	0.48	0.38		L08A	Urethral Procedures W CC	Surgical	1.22	1.08
MDC 04. Diseases and disorders of	E01A	Major Chest Procedures W Catastrophic CC	Surgical	6.36	6.25		L08B	Urethral Procedures W/O CC	Surgical	0.77	0.50

the respiratory system	E01B	Major Chest Procedures W/O Catastrophic CC	Surgical	3.47	3.05		L09A	Other Procedures for Kidney and Urinary Tract Disorders W Catastrophic CC	Surgical	7.46	7.83
	E02A	Other Respiratory System O.R. Procedures W Catastrophic CC	Surgical	4.32	5.00		L09B	Other Procedures for Kidney and Urinary Tract Disorders W Severe CC	Surgical	2.30	1.89
	E02B	Other Respiratory System O.R. Procedures W Severe CC	Surgical	1.83	1.82		L09C	Other Procedures for Kidney and Urinary Tract Disorders W/O Catastrophic or Severe CC	Surgical	1.40	0.79
	E02C	Other Respiratory System O.R. Procedures W/O Catastrophic or Severe CC	Surgical	0.82	0.57		L40Z	Ureteroscopy	Other	0.88	0.48
	E40Z	Respiratory System Diagnosis	Other	5.53	2.54		L41Z	Cystourethroscopy W/O CC	Other	0.43	0.20

		W Ventilator Support									
	E60A	Cystic Fibrosis W Catastrophic or Severe CC	Medical	3.18	4.04		L42Z	ESW Lithotripsy for Urinary Stones	Other	0.43	0.07
	E60B	Cystic Fibrosis W/O Catastrophic or Severe CC	Medical	2.27	2.95		L60A	Renal Failure W Catastrophic CC	Medical	3.48	4.42
	E61A	Pulmonary Embolism W Catastrophic or Severe CC	Medical	2.39	3.00		L60B	Renal Failure W Severe CC or (Age > 69 W/O Severe CC)	Medical	1.46	2.01
	E61B	Pulmonary Embolism W/O Catastrophic or Severe CC	Medical	1.29	1.38		L60C	Renal Failure Age<70 W/O Catastrophic or Severe CC	Medical	0.76	0.91
	E62A	Respiratory Infections/ Inflammations W Catastrophic CC	Medical	2.63	3.66		L61Z	Admit for Renal Dialysis	Medical	0.15	0.21

	E62B	Respiratory Infections/ Inflammations W Severe or Moderate CC	Medical	1.50	2.13		L62A	Kidney and Urinary Tract Neoplasms W Catastrophic or Severe CC	Medical	1.71	2.51
	E62C	Respiratory Infections/ Inflammations W/O CC	Medical	0.87	1.19		L62B	Kidney and Urinary Tract Neoplasms W/O Catastrophic or Severe CC	Medical	0.75	0.90
	E63Z	Sleep Apnoea	Medical	0.58	0.39		L63A	Kidney and Urinary Tract Infections Age>69 W Catastrophic CC	Medical	2.21	3.51
	E64Z	Pulmonary Oedema and Respiratory Failure	Medical	1.69	1.87		L63B	Kidney and Urinary Tract Infections Age>69 W/O Catastrophic CC	Medical	1.02	1.42

	E65A	Chronic Obstructive Airways Disease W Catastrophic or Severe CC	Medical	1.82	2.56		L63C	Kidney and Urinary Tract Infections Age < 70	Medical	0.76	0.90
	E65B	Chronic Obstructive Airways Disease W/O Catastrophic or Severe CC	Medical	1.02	1.35		L64Z	Urinary Stones and Obstruction	Medical	0.50	0.37
	E66A	Major Chest Trauma Age>69 W CC	Medical	2.27	3.05		L65A	Kidney and Urinary Tract Signs and Symptoms W Catastrophic or Severe CC	Medical	1.29	1.79
	E66B	Major Chest Trauma (Age<70 W CC) or (Age>69 W/O CC)	Medical	1.26	1.42		L65B	Kidney and Urinary Tract Signs and Symptoms W/O Catastrophic or Severe CC	Medical	0.48	0.52

	E66C	Major Chest Trauma Age<70 W/O CC)	Medical	0.68	0.61		L66Z	Urethral Stricture	Medical	0.44	0.36
	E67A	Respiratory Signs and Symptoms W Catastrophic or Severe CC	Medical	1.03	1.17		L67A	Other Kidney and Urinary Tract Diagnoses W Catastrophic CC	Medical	2.70	3.47
	E67B	Respiratory Signs and Symptoms Age<3 W/O Catastrophic or Severe CC	Medical	0.56	0.65		L67B	Other Kidney and Urinary Tract Diagnoses W Severe CC	Medical	1.14	1.35
	E67C	Respiratory Signs and Symptoms Age>2 W/O Catastrophic or Severe CC	Medical	0.45	0.30		L67C	Other Kidney and Urinary Tract Diagnoses W/O Catastrophic or Severe CC	Medical	0.47	0.49
	E68Z	Pneumothorax	Medical	1.16	1.30	MDC 12. Diseases and disorders of the male	M01Z	Major Male Pelvic Procedures	Surgical	3.65	3.30
	E69A	Bronchitis and Asthma Age>49 W CC	Medical	1.22	1.73		M02A	Transurethral Prostatectomy W Catastrophic or	Surgical	2.40	2.71

						reproduct-ive system		Severe CC			
	E69B	Bronchitis and Asthma (Age<50 W CC) or (Age>49 W/O CC)	Medical	0.79	0.97		M02B	Transurethral Prostatectomy W/O Catastrophic or Severe CC	Surgical	1.35	1.18
	E69C	Bronchitis and Asthma Age<50 W/O CC	Medical	0.56	0.66		M03A	Penis Procedures W CC	Surgical	2.14	2.13
	E70A	Whooping Cough and Acute Bronchiolitis W Catastrophic or Severe CC	Medical	1.89	2.87		M03B	Penis Procedures W/O CC	Surgical	0.98	0.59
	E70B	Whooping Cough and Acute Bronchiolitis W/O Catastrophic or Severe CC	Medical	0.88	1.36		M04A	Testes Procedures W CC	Surgical	1.63	1.50
	E71A	Respiratory Neoplasms W CC	Medical	1.71	2.35		M04B	Testes Procedures W/O CC	Surgical	0.69	0.34

	E71B	Respiratory Neoplasms W/O CC	Medical	0.90	1.05		M05Z	Circumcision	Surgical	0.54	0.29
	E72Z	Respiratory Problems Arising from Neonatal Period	Medical	2.28	1.94		M06A	Other Male Reproductive System O.R. Procedures for Malignancy	Surgical	2.84	1.52
	E73A	Pleural Effusion W Catastrophic CC	Medical	2.42	3.28		M06B	Other Male Reproductive System O.R. Procedures Except for Malignancy	Surgical	1.02	0.87
	E73B	Pleural Effusion W Severe CC	Medical	1.49	1.90		M40Z	Cystourethroscopy W/O CC	Other	0.28	0.13
	E73C	Pleural Effusion W/O Catastrophic or Severe CC	Medical	0.79	0.83		M60A	Malignancy Male Reproductive System W Catastrophic or Severe CC	Medical	1.79	2.67

	E74A	Interstitial Lung Disease Age>64 W Catastrophic or Severe CC	Medical	2.10	2.80		M60B	Malignancy Male Reproductive System W/O Catastrophic or Severe CC	Medical	0.64	0.68
	E74B	Interstitial Lung Disease (Age<65 W Catastrophic/ Severe CC) or (Age>64 W/O Catastrophic/ Severe CC)	Medical	1.63	2.25		M61A	Benign Prostatic Hypertrophy W Catastrophic or Severe CC	Medical	1.34	1.89
	E74C	Interstitial Lung Disease Age<65 W/O Catastrophic or Severe CC	Medical	0.96	0.98		M61B	Benign Prostatic Hypertrophy W/O Catastrophic or Severe CC	Medical	0.44	0.43
	E75A	Other Respiratory System Diagnosis Age>64 W CC	Medical	1.39	1.99		M62A	Inflammation of the Male Reproductive System W CC	Medical	1.13	1.48

	E75B	Other Respiratory System Diagnosis (Age<65 W CC) or (Age>64 W/O CC)	Medical	0.96	1.17		M62B	Inflammation of the Male Reproductive System W/O CC	Medical	0.53	0.55
	E75C	Other Respiratory System Diagnosis Age<65 W/O CC	Medical	0.57	0.68		M63Z	Sterilisation Male	Medical	0.39	0.16
MDC 05. Diseases and disorders of the circulatory system	F01Z	Implantation or Replacement of AICD Total System	Surgical	5.01	1.49		M64Z	Other Male Reproductive System Diagnoses	Medical	0.38	0.27
	F02Z	AICD Component Implantation/ Replacement	Surgical	8.12	1.59	MDC 13. Diseases and disorders of the female reproduct-ive system	N01Z	Pelvic Evisceration and Radical Vulvectomy	Surgical	4.12	4.98
	F03Z	Cardiac Valve Procedure W Pump W Invasive Cardiac Investigative Procedure	Surgical	13.87	6.58		N02A	Uterine Adnexa Procedure for Ovarian or Adnexal Malignancy W CC	Surgical	4.27	5.30

	F04A	Cardiac Valve Procedure W Pump W/O Invasive Cardiac Investigative Procedure W Catastrophic or Severe CC	Surgical	9.29	4.13		N02B	Uterine Adnexa Procedure for Ovarian or Adnexal Malignancy W/O CC	Surgical	2.25	2.28
	F04B	Cardiac Valve Procedure W Pump W/O Invasive Cardiac Investigative Procedure W/O Catastrophic or Severe CC	Surgical	7.11	2.56		N03A	Uterine Adnexa Procedure for Non−Ovarian or Adnexal Malignancy W CC	Surgical	3.80	4.40
	F05A	Coronary Bypass W Invasive Cardiac Investigative Procedure W Catastrophic CC	Surgical	9.79	4.92		N03B	Uterine Adnexa Procedure for Non−Ovarian or Adnexal Malignancy W/O CC	Surgical	2.21	2.27

	F05B	Coronary Bypass W Invasive Cardiac Investigative Procedure W/O Catastrophic CC	Surgical	7.22	3.24		N04Z	Hysterectomy for Non−Malignancy	Surgical	1.81	1.66
	F06A	Coronary Bypass W/O Invasive Cardiac Investigative Procedure W Catastrophic or Severe CC	Surgical	6.49	3.52		N05A	Oophorectomies and Complex Fallopian Tube Procedures for Non−Malignancy W Catastrophic or Severe CC	Surgical	2.75	2.90
	F06B	Coronary Bypass W/O Invasive Cardiac Investigative Procedure W/O Catastrophic or Severe CC	Surgical	4.78	2.12		N05B	Oophorectomies and Complex Fallopian Tube Procedures for Non−Malignancy W/O Catastrophic or Severe CC	Surgical	1.59	1.28
	F07Z	Other Cardiothoracic/ Vascular	Surgical	9.51	4.74		N06Z	Female Reproductive System	Surgical	1.41	1.30

		Procedures W Pump						Reconstructive Procedures			
	F08A	Major Reconstruct Vascular Procedures W/O Pump W Catastrophic CC	Surgical	8.40	7.41		N07Z	Other Uterine and Adnexa Procedures for Non−Malignancy	Surgical	0.81	0.34
	F08B	Major Reconstruct Vascular Procedures W/O Pump W/O Catastrophic CC	Surgical	4.09	2.97		N08Z	Endoscopic Procedures for Female Reproductive System	Surgical	0.66	0.21
	F09Z	Other Cardiothoracic Procedures W/O Pump	Surgical	5.58	2.64		N09Z	Conisation Vagina Cervix and Vulva Procedures	Surgical	0.51	0.25
	F10Z	Percutaneous Coronary Angioplasty W AMI	Surgical	2.98	0.75		N10Z	Diagnostic Curettage or Diagnostic Hysteroscopy	Surgical	0.46	0.17

	F11A	Amputation for Circulatory System Except Upper Limb and Toe W Catastrophic CC	Surgical	9.30	2.40		N11A	Other Female Reproductive System O.R. Procedures Age>64 or W Malignancy or W CC	Surgical	2.50	2.74
	F11B	Amputation for Circulatory System Except Upper Limb and Toe W/O Catastrophic CC	Surgical	4.56	5.80		N11B	Other Female Reproductive System O.R. Procedures Age<65 W/O Malignancy W/O CC	Surgical	0.70	0.34
	F12Z	Cardiac Pacemaker Implantation	Surgical	3.37	1.14		N60A	Malignancy Female Reproductive System W Catastrophic or Severe CC	Medical	1.80	2.71

	F13Z	Upper Limb and Toe Amputation for Circulatory System Disorders	Surgical	3.72	4.64		N60B	Malignancy Female Reproductive System W/O Catastrophic or Severe CC	Medical	0.89	1.21
	F14A	Vascular Procedures Except Major Reconstruction W/O Pump W Catastrophic CC	Surgical	5.05	4.77		N61Z	Infections Female Reproductive System	Medical	0.56	0.66
	F14B	Vascular Procedures Except Major Reconstruction W/O Pump W Severe CC	Surgical	2.17	1.52		N62A	Menstrual and Other Female Reproductive System Disorders W CC	Medical	0.63	0.73
	F14C	Vascular Procedures Except Major Reconstruction W/O Pump W/O	Surgical	1.58	0.95		N62B	Menstrual and Other Female Reproductive System Disorders W/O CC	Medical	0.28	0.23

		Catastrophic or Severe CC									
	F15Z	Percutaneous Coronary Angioplasty W/O AMI W Stent Implantation	Surgical	2.06	0.56	MDC 14. Pregnancy, childbirth and the puerperium	O01A	Caesarean Delivery W Multiple Complicating Diagnoses At Least One Severe	Surgical	3.25	5.68
	F16Z	Percutaneous Coronary Angioplasty W/O AMI W/O Stent Implantation	Surgical	1.69	0.56		O01B	Caesarean Delivery W Severe Complicating Diagnosis	Surgical	2.26	3.58
	F17Z	Cardiac Pacemaker Replacement	Surgical	2.51	0.71		O01C	Caesarean Delivery W Moderate Complicating Diagnosis	Surgical	2.10	3.14

	F18Z	Cardiac Pacemaker Revision Except Device Replacement	Surgical	2.03	1.20		O01D	Caesarean Delivery W/O Complicating Diagnosis	Surgical	1.85	2.79
	F19Z	Other Trans−Vascular Percutaneous Cardiac Intervention	Surgical	2.18	0.89		O02Z	Vaginal Delivery W Complicating O.R. Procedure	Surgical	1.80	2.65
	F20Z	Vein Ligation and Stripping	Surgical	0.97	0.49		O03Z	Ectopic Pregnancy	Surgical	1.09	0.72
	F21A	Other Circulatory System O.R. Procedures W Catastrophic CC or (Age>64 W/O Catastrophic CC)	Surgical	3.85	4.26		O04Z	Postpartum and Post Abortion W O.R. Procedure	Surgical	0.84	0.70
	F21B	Other Circulatory System O.R. Procedures Age<65 W/O Catastrophic CC	Surgical	1.70	1.41		O40Z	Abortion W D&C Aspiration Curettage or Hysterotomy	Other	0.47	0.23

	F40Z	Circulatory System Diagnosis W Ventilator Support	Other	4.91	1.72		O60A	Vaginal Delivery W Multiple Complicating Diagnosis At Least One Severe	Medical	1.63	3.19
	F41A	Circulatory Disorders W AMI W Invasive Cardiac Investigative Procedure W Catastrophic or Severe CC	Other	2.86	1.60		O60B	Vaginal Delivery W Severe Complicating Diagnosis	Medical	1.25	2.48
	F41B	Circulatory Disorders W AMI W Invasive Cardiac Investigative Procedure W/O Catastrophic or Severe CC	Other	1.72	0.84		O60C	Vaginal Delivery W Moderate Complicating Diagnosis	Medical	1.18	2.40

	F42A	Circulatory Disorders W/O AMI W Invasive Cardiac Investigative Procedure W Complex DX/Pr	Other	1.74	1.00		O60D	Vaginal Delivery W/O Complicating Diagnosis	Medical	0.98	1.97
	F42B	Circulatory Disorders W/O AMI W Invasive Cardiac Investigative Procedure W/O Complex DX/Pr	Other	0.80	0.39		O61Z	Postpartum and Post Abortion W/O O.R. Procedure	Medical	0.54	0.87
	F60A	Circulatory Disorders W AMI W/O Invasive Cardiac Investigative Procedure W Catastrophic or Severe CC	Medical	2.20	2.15		O62Z	Threatened Abortion	Medical	0.31	0.30

	F60B	Circulatory Disorders W AMI W/O Invasive Cardiac Investigative Procedure W/O Catastrophic or Severe CC	Medical	1.17	0.73		O63Z	Abortion W/O D&C Aspiration Curettage or Hysterotomy	Medical	0.39	0.38
	F60C	Circulatory Disorders W AMI W/O Invasive Cardiac Investigative Procedure Died	Medical	1.31	1.13		O64Z	False Labour	Medical	0.37	0.66
	F61Z	Infective Endocarditis	Medical	3.76	4.51		O65A	Other Antenatal Admission W Severe Complicating Diagnosis	Medical	0.43	0.69
	F62A	Heart Failure and Shock W Catastrophic CC	Medical	2.58	3.44		O65B	Other Antenatal Admission W Moderate or No Complicating	Medical	0.35	0.54

								Diagnosis			
	F62B	Heart Failure and Shock W/O Catastrophic CC	Medical	1.18	1.50	MDC 15. Newborns and other neonates	P01Z	Neonate, Died or Transferred <5 Days of Admission W Significant OR Procedure	Surgical	1.51	0.07
	F63A	Venous Thrombosis W Catastrophic or Severe CC	Medical	1.96	2.92		P02Z	Cardiothoracic/ Vascular Procedures for Neonates	Surgical	24.01	10.70
	F63B	Venous Thrombosis W/O Catastrophic or Severe CC	Medical	0.89	1.15		P03Z	Neonate Admitted W 1000−1499 g W Significant O.R. Procedure	Surgical	21.25	4.43
	F64Z	Skin Ulcers for Circulatory Disorders	Medical	1.88	2.94		P04Z	Neonate, Admitted W < 1500-1999 g W Significant OR Procedure	Surgical	12.94	3.67

	F65A	Peripheral Vascular Disorders W Catastrophic or Severe CC	Medical	2.07	2.81		P05Z	Neonate, Admitted W < 2000-2499 g W significant OR procedure	Surgical	13.51	7.73
	F65B	Peripheral Vascular Disorders W/O Catastrophic or Severe CC	Medical	0.71	0.59		P06A	Neonate, Admitted W > 2499 g W Significant OR Procedure W Multi Major Problems	Surgical	15.07	6.15
	F66A	Coronary Atherosclerosis W CC	Medical	0.92	1.02		P06B	Neonate Admitted W >2499 g W Significant O.R. Procedure W/O Multi Major Problems	Surgical	4.89	1.78
	F66B	Coronary Atherosclerosis W/O CC	Medical	0.46	0.35		P60A	Neonate Died or Transferred <5 Days of Admission W/O Significant O.R. Procedure Born Here	Medical	0.60	0.43
	F67A	Hypertension W CC	Medical	1.07	1.27		P60B	Neonate Died/Transferred	Medical	0.92	0.42

								<5 Days of Admission W/O Significant O.R. Procedure Not Born Here			
	F67B	Hypertension W/O CC	Medical	0.55	0.59		P61Z	Neonate, Admitted W < 750 g	Medical	38.96	5.39
	F68Z	Congenital Heart Disease	Medical	0.68	0.68		P62Z	Neonate, Admitted W 750-999 g	Medical	27.19	6.94
	F69A	Valvular Disorders W Catastrophic or Severe CC	Medical	1.55	1.47		P63Z	Neonate Admitted W 1000−1249 g W/O Significant O.R. Procedure	Medical	11.59	3.03
	F69B	Valvular Disorders W/O Catastrophic or Severe CC	Medical	0.40	0.28		P64Z	Neonate Admitted W 1250−1499 g W/O Significant O.R. Procedure	Medical	8.27	4.90
	F70A	Major Arrhythmia and Cardiac Arrest W Catastrophic or Severe CC	Medical	1.93	1.35		P65A	Neonate, Admitted W < 1500-1999 g W/O Significant OR Procedure W Multi Major	Medical	8.93	2.67

								Problems			
	F70B	Major Arrhythmia and Cardiac Arrest W/O Catastrophic or Severe CC	Medical	0.89	0.42		P65B	Neonate Admitted With 1500−1999 g W/O Significant O.R. Procedure W Major Problem	Medical	6.25	4.15
	F71A	Non−Major Arrhythmia and Conduction Disorders W Catastrophic or Severe CC	Medical	1.50	1.72		P65C	Neonate Admitted W 1500−1999 g W/O Significant O.R. Procedure W Other Problem	Medical	4.31	3.74
	F71B	Non−Major Arrhythmia and Conduction Disorders W/O Catastrophic or Severe CC	Medical	0.61	0.48		P65D	Neonate Admitted W 1500−1999 g W/O Significant O.R. Procedure W/O Problem	Medical	3.45	4.92

	F72A	Unstable Angina W Catastrophic or Severe CC	Medical	1.30	1.37		P66A	Neonate Admitted W 2000−2499 g W/O Significant O.R. Procedure W Multi Major Problems	Medical	6.08	3.76
	F72B	Unstable Angina W/O Catastrophic or Severe CC	Medical	0.71	0.54		P66B	Neonate Admitted W 2000−2499 g W/O Significant O.R. Procedure W Major Problem	Medical	3.97	3.60
	F73A	Syncope and Collapse W Catastrophic or Severe CC	Medical	1.26	1.66		P66C	Neonate Admitted W 2000−2499 g W/O Significant O.R. Procedure W Other Problem	Medical	2.59	2.97
	F73B	Syncope and Collapse W/O Catastrophic or Severe CC	Medical	0.47	0.41		P66D	Neonate Admitted W 2000−2499 g W/O Significant O.R. Procedure W/O Problem	Medical	1.52	2.05
	F74Z	Chest Pain	Medical	0.43	0.25		P67A	Neonate Admitted W > 2499 g W/O	Medical	4.00	2.44

								Significant O.R. Procedure W Multi Major Problems			
	F75A	Other Circulatory System Diagnoses W Catastrophic CC	Medical	2.75	3.18		P67B	Neonate Admitted W > 2499 g W/O Significant O.R. Procedure W Major Problem	Medical	2.34	2.01
	F75B	Other Circulatory System Diagnoses W Severe CC	Medical	1.48	1.59		P67C	Neonate Admitted W > 2499 g W/O Significant O.R. Procedure W Other Problem	Medical	1.12	1.47
	F75C	Other Circulatory System Diagnoses W/O Catastrophic or Severe CC	Medical	0.84	0.68		P67D	Neonate Admitted W > 2499 g W/O Significant O.R. Procedure W/O Problem	Medical	0.57	0.91
MDC 06. Diseases and disorders of	G01A	Rectal Resection W Catastrophic CC	Surgical	7.35	7.21	MDC 16. Diseases and	Q01Z	Splenectomy	Surgical	3.77	3.18

the digestive system	G01B	Rectal Resection W/O Catastrophic CC	Surgical	4.34	3.83	disorders of the blood and blood-forming organs and immune-logical disorders	Q02A	Other O.R. Procedure of Blood and Blood Forming Organs W Catastrophic or Severe CC	Surgical	5.44	5.85
	G02A	Major Small and Large Bowel Procedures W Catastrophic CC	Surgical	7.14	6.69		Q02B	Other O.R. Procedure of Blood and Blood Forming Organs W/O Catastrophic or Severe CC	Surgical	0.90	0.56
	G02B	Major Small and Large Bowel Procedures W/O Catastrophic CC	Surgical	3.35	3.02		Q60A	Reticulo-endothelial and Immunity Disorders W Catastrophic or Severe CC	Medical	2.22	3.02
	G03A	Stomach Oesophageal and Duodenal Procedures W Malignancy	Surgical	7.82	7.04		Q60B	Reticulo-endothelial and Immunity Disorders W/O Catastrophic or	Medical	0.47	0.47

								Severe CC			
	G03B	Stomach Oesophageal and Duodenal Procedures W/O Malignancy W Catastrophic or Severe CC	Surgical	6.08	4.83		Q61A	Red Blood Cell Disorders W Catastrophic CC	Medical	1.82	2.49
	G03C	Stomach Oesophageal and Duodenal Procedures W/O Malignancy W/O Catastrophic or Severe CC	Surgical	2.23	1.74		Q61B	Red Blood Cell Disorders W Severe CC	Medical	1.00	1.28
	G04A	Peritoneal Adhesiolysis Age>49 W CC	Surgical	5.02	5.06		Q61C	Red Blood Cell Disorders W/O Catastrophic or Severe CC	Medical	0.38	0.34

	G04B	Peritoneal Adhesiolysis (Age<50 W CC) or (Age>49 W/O CC)	Surgical	2.73	2.69		Q62A	Coagulation Disorders Age>69	Medical	0.93	1.11
	G04C	Peritoneal Adhesiolysis Age<50 W/O CC	Surgical	1.61	1.34		Q62B	Coagulation Disorders Age<70	Medical	0.68	0.68
	G05A	Minor Small and Large Bowel Procedures W CC	Surgical	2.50	2.71	MDC 17. Neoplastic disorders (haemato-logical and solid neoplasms)	R01A	Lymphoma and Leukaemia W Major O.R. Procedures W Catastrophic or Severe CC	Surgical	8.39	8.38
	G05B	Minor Small and Large Bowel Procedures W/O CC	Surgical	0.94	0.63		R01B	Lymphoma and Leukaemia W Major O.R. Procedures W/O Catastrophic or Severe CC	Surgical	2.84	2.43
	G06Z	Pyloromyotomy Procedure	Surgical	1.62	1.61		R02A	Other Neoplastic Disorders W Major O.R. Procedures W Catastrophic or	Surgical	4.60	4.34

								Severe CC			
	G07A	Appendicectomy W Catastrophic or Severe CC	Surgical	2.49	2.46		R02B	Other Neoplastic Disorders W Major O.R. Procedures W/O Catastrophic or Severe CC	Surgical	2.17	1.78
	G07B	Appendicectomy W/O Catastrophic or Severe CC	Surgical	1.32	1.06		R03A	Lymphoma and Leukaemia W Other O.R. Procedures W Catastrophic or Severe CC	Surgical	7.57	8.22
	G08Z	Abdominal Umbilical and Other Hernia Procedures Age>0	Surgical	1.19	0.81		R03B	Lymphoma and Leukaemia W Other O.R. Procedures W/O Catastrophic or Severe CC	Surgical	1.47	0.96
	G09Z	Inguinal and Femoral Hernia Procedures Age>0	Surgical	0.91	0.49		R04A	Other Neoplastic Disorders W Other O.R. Procedures W Catastrophic or	Surgical	2.44	2.32

								Severe CC			
	G10Z	Hernia Procedures Age<1	Surgical	0.86	0.60		R04B	Other Neoplastic Disorders W Other O.R. Procedures W/O Catastrophic or Severe CC	Surgical	1.09	0.43
	G11A	Anal and Stomal Procedures W Catastrophic or Severe CC	Surgical	1.58	1.47		R60A	Acute Leukaemia W Catastrophic CC	Medical	7.13	8.03
	G11B	Anal and Stomal Procedures W/O Catastrophic or Severe CC	Surgical	0.68	0.43		R60B	Acute Leukaemia W Severe CC	Medical	1.73	1.93
	G12A	Other Digestive System O.R. Procedures W Catastrophic or Severe CC or W Malignancy	Surgical	3.58	3.45		R60C	Acute Leukaemia W/O Catastrophic or Severe CC	Medical	0.93	1.08

	G12B	Other Digestive System O.R. Procedures W/O Catastrophic or Severe CC W/O Malignancy	Surgical	1.26	0.91		R61A	Lymphoma and Non−Acute Leukaemia W Catastrophic CC	Medical	4.55	5.76
	G40A	Complex Therapeutic Gastroscopy for Major Digestive Disease W Catastrophic or Severe CC Procedure	Other	2.76	2.98		R61B	Lymphoma and Non−Acute Leukaemia W/O Catastrophic CC	Medical	1.61	1.86
	G40B	Complex Therapeutic Gastroscopy for Major Digestive Disease W/O Catastrophic or Severe CC Procedure	Other	1.12	1.13		R61C	Lymphoma and Non−Acute Leukaemia Same-day	Medical	0.22	0.15

	G41A	Complex Therapeutic Gastroscopy for Non−Major Digestive Diseases	Other	1.80	2.28		R62A	Other Neoplastic Disorders W CC	Medical	1.81	2.50
	G41B	Complex Therapeutic Gastroscopy for Non−Major Digestive Diseases Same-day	Other	0.33	0.11		R62B	Other Neoplastic Disorders W/O CC	Medical	0.67	0.66
	G42A	Other Gastroscopy for Major Digestive Disease	Other	1.58	1.77		R63Z	Chemotherapy	Medical	0.24	0.16
	G42B	Other Gastroscopy for Major Digestive Disease Same-day	Other	0.34	0.11		R64Z	Radiotherapy	Medical	0.42	0.23
	G43Z	Complex Therapeutic Colonoscopy	Other	0.54	0.36	MDC 18. Infectious and	S60Z	HIV Same-day	Medical	0.26	0.16

	G44A	Other Colonoscopy W Catastrophic or Severe CC or Complicating Procedure	Other	1.82	2.12	parasitic diseases	S61Z	HIV-related CNS disease	Medical	4.49	4.65
	G44B	Other Colonoscopy W/O Catastrophic or Severe CC or Complicating Procedure	Other	1.02	1.05		S62Z	HIV-Related Malignancy	Medical	4.47	4.66
	G44C	Other Colonoscopy Same-day	Other	0.37	0.13		S63A	HIV-Related Infection W Catastrophic CC	Medical	9.26	7.76
	G45A	Other Gastroscopy for Non−Major Digestive Disease	Other	1.20	1.29		S63B	HIV−Related Infection W/O Catastrophic CC	Medical	2.90	2.80
	G45B	Other Gastroscopy for Non−Major Digestive Disease Same-day	Other	0.30	0.11		S64A	Other HIV W Catastrophic CC	Medical	4.94	5.39

	G60A	Digestive Malignancy W Catastrophic or Severe CC	Medical	1.56	2.43		S64B	Other HIV W/O Catastrophic cc	Medical	1.97	2.28
	G60B	Digestive Malignancy W/O Catastrophic or Severe CC	Medical	0.79	1.01		T01A	O.R. Procedures for Infectious and Parasitic Diseases W Catastrophic CC	Surgical	8.44	8.85
	G61A	GI Haemorrhage (Age<65 W Catastrophic or Severe CC) or Age>64	Medical	0.84	1.05		T01B	O.R. Procedures for Infectious and Parasitic Diseases W Severe or Moderate CC	Surgical	2.90	3.17
	G61B	GI Haemorrhage Age<65 W/O Catastrophic or Severe CC	Medical	0.41	0.36		T01C	O.R. Procedures for Infectious and Parasitic Diseases W/O CC	Surgical	1.57	1.63
	G62Z	Complicated Peptic Ulcer	Medical	1.31	1.77		T60A	Septicaemia W Catastrophic or Severe CC	Medical	2.68	3.22

	G63Z	Uncomplicated Peptic Ulcer	Medical	0.36	0.29		T60B	Septicaemia W/O Catastrophic or Severe CC	Medical	1.25	1.70
	G64Z	Inflammatory Bowel Disease	Medical	0.80	0.88		T61A	Postoperative and Post−Traumatic Infect W Catastrophic/ Severe CC or (Age>54 W/O Catastrophic/ Severe CC)	Medical	1.39	1.98
	G65A	GI Obstruction W CC	Medical	1.44	2.03		T61B	Postoperative and Post−Traumatic Infections Age<55 W/O Catastrophic or Severe CC	Medical	0.77	1.02
	G65B	GI Obstruction W/O CC	Medical	0.70	0.88		T62A	Fever of Unknown Origin W CC	Medical	1.20	1.50
	G66A	Abdominal Pain or Mesenteric Adenitis W CC	Medical	0.76	0.82		T62B	Fever of Unknown Origin W/O CC	Medical	0.57	0.61

	G66B	Abdominal Pain or Mesenteric Adenitis W/O CC	Medical	0.39	0.31		T63A	Viral Illness Age>59	Medical	0.79	0.98
	G67A	Oesophagitis Gastroent and Miscellaneous Digestive System Disorders Age>9 W Catastrophic/ Severe CC	Medical	1.23	1.71		T63B	Viral Illness Age<60	Medical	0.55	0.60
	G67B	Oesophagitis Gastroent and Miscellaneous Digestive System Disorders Age>9 W/O Catastrophic/ Severe CC	Medical	0.45	0.44		T64A	Other Infectious and Parasitic Diseases W Catastrophic or Severe CC	Medical	2.41	2.89
	G68A	Gastroenteritis Age<10 W CC	Medical	0.99	1.26		T64B	Other Infectious and Parasitic Diseases W/O Catastrophic or Severe CC	Medical	0.79	0.90

	G68B	Gastroenteritis Age<10 W/O CC	Medical	0.53	0.70	MDC 19. Mental diseases and disorders	U40Z	Mental Health Treatment Same-day W ECT	Other	0.23	0.51
	G69Z	Oesophagitis and Miscellaneous Digestive System Disorders Age<10	Medical	0.61	0.79		U60Z	Mental Health Treatment Same-day W/O ECT	Medical	0.21	0.12
	G70A	Other Digestive System Diagnoses W CC	Medical	1.21	1.51		U61A	Schizophrenia Disorders w Mental Health Legal Status	Medical	4.11	8.63
	G70B	Other Digestive System Diagnoses W/O CC	Medical	0.39	0.35		U61B	Schizophrenia Disorders W/O Mental Health Legal Status	Medical	2.09	3.87
MDC 07. Diseases and disorders of the hepatobiliary system and pancreas	H01A	Pancreas Liver and Shunt Procedures W Catastrophic CC	Surgical	8.47	7.38		U62A	Paranoia, Acute Psychological Disorder W Catastrophic/ Severe CC/W Mental Health Legal Status	Medical	3.55	7.34

	H01B	Pancreas Liver and Shunt Procedures W Severe or Moderate CC	Surgical	4.20	3.16		U62B	Paranoia and Acute Psych Disorder W/O Catastrophic/ Severe CC W/O Mental Health Legal Status	Medical	1.53	2.42
	H01C	Pancreas Liver and Shunt Procedures W/O CC	Surgical	3.15	2.35		U63A	Major Affective Disorders W Catastrophic or Severe CC or (Age>69 W/O Catastrophic or Severe CC)	Medical	3.73	6.83
	H02A	Major Biliary Tract Procedures W Malignancy	Surgical	6.66	7.01		U63B	Major Affective Disorders Age<70 W/O Catastrophic or Severe CC	Medical	2.43	4.50
	H02B	Major Biliary Tract Procedures W/O Malignancy W Catastrophic or Severe CC	Surgical	5.58	5.24		U64Z	Other Affective and Somatoform Disorders	Medical	1.15	1.92

	H02C	Major Biliary Tract Procedures W/O Malignancy W/O Catastrophic or Severe CC	Surgical	2.17	1.65		U65Z	Anxiety Disorders	Medical	0.88	1.35
	H03A	Cholecystectomy W Closed CDE W Catastrophic or Severe CC	Surgical	4.65	3.92		U66Z	Eating and Obsessive Compulsive Disorders	Medical	4.46	8.19
	H03B	Cholecystectomy W Closed CDE W/O Catastrophic or Severe CC	Surgical	2.52	1.68		U67Z	Personality Disorders and Acute Reactions	Medical	1.17	1.95
	H04A	Cholecystectomy W/O Closed CDE W Catastrophic or Severe CC	Surgical	2.99	2.59		U68Z	Childhood Mental Disorders	Medical	2.88	4.56

	H04B	Cholecystectomy W/O Closed CDE W/O Catastrophic or Severe CC	Surgical	1.37	0.78	MDC 20. Alcohol/ drug use and alcohol/ drug-induced organic mental disorders	V60Z	Alcohol Intoxication and Withdrawal	Medical	0.49	0.50
	H05A	Hepatobiliary Diagnostic Procedures W Catastrophic or Severe CC	Surgical	3.98	3.69		V61A	Drug Intoxication and Withdrawal W CC	Medical	1.41	2.43
	H05B	Hepatobiliary Diagnostic Procedures W/O Catastrophic or Severe CC	Surgical	1.55	1.42		V61B	Drug Intoxication and Withdrawal WO CC	Medical	1.17	2.10
	H06Z	Other Hepatobiliary and Pancreas O.R. Procedures	Surgical	4.34	4.51		V62A	Alcohol Use Disorder and Dependence	Medical	1.01	1.64
	H40Z	Endoscopic Procedures for Bleeding Oesophageal	Other	2.75	2.60		V62B	Alcohol Use Disorder and Dependence Same-day	Medical	0.23	0.13

		Varices									
	H41A	ERCP Complex Therapeutic Procedure W Catastrophic or Severe CC	Other	3.35	3.94		V63Z	Opioid Use Disorder and Dependence	Medical	0.81	1.25
	H41B	ERCP Complex Therapeutic Procedure W/O Catastrophic or Severe CC	Other	1.12	0.90		V64Z	Other Drug Use Disorder and Dependence	Medical	0.65	1.00
	H42A	ERCP Other Therapeutic Procedure W Catastrophic or Severe CC	Other	276	3.15	MDC 21. Injuries, poisoning and toxic effects of drugs	W01Z	Ventilation or Craniotomy Procedures for Multiple Significant Trauma	Surgical	22.68	9.71
	H42B	ERCP Other Therapeutic Procedure W/O Catastrophic or	Other	0.98	0.80		W02Z	Hip Femur and Limb Procedures for Multiple Significant Trauma	Surgical	8.91	6.53

		Severe CC						Including Implantation			
	H60A	Cirrhosis and Alcoholic Hepatitis W Catastrophic CC	Medical	3.04	3.79		W03Z	Abdominal Procedures for Multiple Significant Trauma	Surgical	6.42	4.78
	H60B	Cirrhosis and Alcoholic Hepatitis W Catastrophic or Severe CC	Medical	1.32	1.57		W04Z	Other O.R. Procedures for Multiple Significant Trauma	Surgical	7.74	6.75
	H60C	Cirrhosis and Alcoholic Hepatitis W/O Catastrophic or Severe CC	Medical	0.66	0.68		W60Z	Multiple Trauma Died or Transferred to Another Acute Care Facility LOS<5 Days	Medical	2.17	0.21

	H61A	Malignancy of Hepatobiliary System Pancreas Age>69 W Catastrophic or Severe CC	Medical	2.13	3.42		W61Z	Multiple Trauma Without Significant Procedures	Medical	3.12	3.47
	H61B	Malignancy of Hepatobiliary System Pancreas (A<70 W Catastrophic/ Severe CC) or (A>69 W/O Catastrophic/ Severe CC)	Medical	1.45	1.82		X01Z	Microvascular Tissue Transfer or Skin Grafts for Injuries to Lower Limb	Surgical	3.63	4.74
	H61C	Malignancy of Hepatobiliary System Pancreas Age<70 W/O Catastrophic or Severe CC	Medical	0.83	0.84		X02Z	Microvascular Tissue Transfer or Skin Grafts for Injuries to Hand	Surgical	1.35	0.86

	H62A	Disorders of Pancreas Except for Malignancy W Catastrophic or Severe CC	Medical	2.30	2.67		X03Z	Microvascular Tissue Transfer or Skin Grafts for Other Injuries	Surgical	2.90	2.82
	H62B	Disorders of Pancreas Except for Malignancy W/O Catastrophic or Severe CC	Medical	0.92	1.08		X04A	Other Procedures for Injuries to Lower Limb Age>59 or W CC	Surgical	4.03	4.05
	H63A	Disorders of Liver Except Malignancy Cirrhosis Alcoholic Hepatitis W Catastrophic/ Severe CC	Medical	2.37	2.93		X04B	Other Procedures for Injuries to Lower Limb Age<60 W/O CC	Surgical	1.20	0.78

	H63B	Disorders of Liver Except Malignancy Cirrhosis Alcoholic Hepatitis W/O Catastrophic/Severe CC	Medical	0.62	0.61		X05Z	Other Procedures for Injuries to Hand	Surgical	0.93	0.50
	H64A	Disorders of the Biliary Tract W CC	Medical	1.31	1.56		X06A	Other Procedures for Other Injuries W Catastrophic or Severe CC	Surgical	3.37	3.14
	H64B	Disorders of the Biliary Tract W/O CC	Medical	0.56	0.55		X06B	Other Procedures for Other Injuries W/O Catastrophic or Severe CC	Surgical	0.97	0.66
MDC 08. Diseases and disorders of the musculo-	I01Z	Bilateral or Multiple Major Joint Procedures of Lower Extremity	Surgical	8.96	5.04		X60A	Injuries Age>64 W CC	Medical	1.27	1.82

skeletal system and connective tissue	I02A	Microvascular Tissue Transfer or (Skin Graft W Catastrophic or Severe CC) Excluding Hand	Surgical	10.35	10.52		X60B	Injuries Age>64 W/O CC	Medical	0.46	0.46
	I02B	Skin Graft W/O Catastrophic or Severe CC Excluding Hand	Surgical	3.65	3.14		X60C	Injuries Age < 65	Medical	0.37	0.24
	I03A	Hip Revision W Catastrophic or Severe CC	Surgical	9.64	6.64		X61Z	Allergic Reactions	Medical	0.42	0.25
	I03B	Hip Replacement W Catastrophic or Severe CC or Hip Revision W/O Catastrophic or Severe CC	Surgical	5.72	4.56		X62A	Poisoning/Toxic Effects of Drugs and Other Substances Age>59 or W CC	Medical	0.94	0.77
	I03C	Hip Replacement W/O Catastrophic or Severe CC	Surgical	4.46	2.68		X62B	Poisoning/Toxic Effects of Drugs and Other Substances	Medical	0.40	0.25

								Age<60 W/O CC			
	I04A	Knee Replacement and Reattachment W Catastrophic CC	Surgical	6.65	4.77		X63A	Sequelae of Treatment W Catastrophic or Severe CC	Medical	1.51	1.99
	I04B	Knee Replacement and Reattachment W/O Catastrophic CC	Surgical	4.62	2.52		X63B	Sequelae of Treatment W/O Catastrophic or Severe CC	Medical	0.59	0.66
	I05Z	Other Major Joint Replacement and Limb Reattachment Procedures	Surgical	4.06	2.12		X64A	Other Injury Poisoning and Toxic Effect Diagnosis Age>59 or W CC	Medical	1.03	1.07
	I06Z	Spinal Fusion W Deformity	Surgical	8.62	4.94		X64B	Other Injury Poisoning and Toxic Effect Diagnosis Age<60 W/O CC	Medical	0.36	0.24
	I07Z	Amputation	Surgical	6.39	7.70	MDC 22.	Y01Z	Severe full	Surgical	36.66	20.13

						Burns		thickness burns			
	I08A	Other Hip and Femur Procedures W Catastrophic or Severe CC	Surgical	4.97	5.42		Y02A	Other Burns W Skin Graft Age>64 or W Catastrophic/ Severe CC or W Complicating Diagnosis/ Procedure	Surgical	8.87	11.52
	I08B	Other Hip and Femur Procedures Age>54 W/O Catastrophic or Severe CC	Surgical	3.11	3.00		Y02B	Other burns w skin graft age<65 w/o Catastrophic or Severe CC W/O Complicated Diagnosis/ Procedure	Surgical	3.15	3.90
	I08C	Other Hip and Femur Procedures Age<55 W/O Catastrophic or Severe CC	Surgical	2.75	2.36		Y03Z	Other O.R. Procedures for Other Burns	Surgical	1.88	1.95
	I09A	Spinal Fusion W Catastrophic or Severe CC	Surgical	9.03	6.92		Y60Z	Burns, transferred to another acute care facility < 5	Surgical	0.59	0.30

								days			
	I09B	Spinal Fusion W/O Catastrophic or Severe CC	Surgical	4.46	2.64		Y61Z	Severe burns	Surgical	1.50	2.66
	I10A	Other Back and Neck Procedures W Catastrophic or Severe CC	Surgical	4.52	4.74		Y62A	Other Burns Age>64 or W Catastrophic or Severe CC or W Complicating Diagnosis/ Procedure	Medical	1.60	2.51
	I10B	Other Back and Neck Procedures W/O Catastrophic or Severe CC	Surgical	2.27	1.88		Y62B	Other Burns Age<65 W/O Catastrophic or Severe CC W/O Complicating Diagnosis/ Procedure	Medical	0.72	1.34
	I11Z	Limb Lengthening Procedures	Surgical	2.60	2.21	MDC 23. Factors influencing	Z01A	O.R. Procedures W Diagnoses of Other Contacts W Health	Surgical	2.00	1.66

						health status and other contacts with health services		Services W Catastrophic/ Severe CC			
	I12A	Infection/ Inflammation of Bone and Joint W Miscellaneous Musculoskeletal System and Connective Tissue Procedures W Catastrophic CC	Surgical	6.34	7.69		Z01B	O.R. Procedures W Diagnoses Other Contacts W Health Services W/O Catastrophic/ Severe CC	Surgical	0.76	0.30
	I12B	Infection/ Inflammation of Bone and Joint W Miscellaneous Musculoskeletal System and Connective Tissue Procedures W Severe CC	Surgical	3.09	3.45		Z40Z	Follow Up After Completed Treatment W Endoscopy	Other	0.31	0.12

	I12C	Infection/ Inflammation of Bone and Joint W Miscellaneous Musculoskeletal System and Connective Tissue Procedures W/O Catastrophic or Severe CC	Surgical	1.75	1.59		Z60A	Rehabilitation W Catastrophic or Severe CC	Medical	5.07	6.04
	I13A	Humerus Tibia Fibula and Ankle Procedures W Catastrophic or Severe CC	Surgical	4.53	4.40		Z60B	Rehabilitation W/O Catastrophic or Severe CC	Medical	1.86	2.46
	I13B	Humerus Tibia Fibula and Ankle Procedures Age>59 W/O Catastrophic or Severe CC	Surgical	242	2.02		Z60C	Rehabilitation Same-day	Medical	1.52	2.18

	I13C	Humerus Tibia Fibula and Ankle Procedures Age<60 W/O Catastrophic or Severe CC	Surgical	1.84	1.24		Z61Z	Signs and Symptoms	Medical	0.71	0.83
	I14Z	Stump Revision	Surgical	3.09	3.96		Z62Z	Follow Up After Completed Treatment W/O Endoscopy	Medical	0.26	0.18
	I15Z	Cranio−Facial Surgery	Surgical	3.37	2.38		Z63A	Other Aftercare W Catastrophic or Severe CC	Medical	2.22	4.12
	I16Z	Other Shoulder Procedures	Surgical	1.38	0.70		Z63B	Other Aftercare W/O Catastrophic or Severe CC	Medical	0.73	1.12
	I17Z	Maxillo−Facial Surgery	Surgical	2.02	1.16		Z64A	Other Factors Influencing Health Status Age>79	Medical	1.39	2.66
	I18Z	Knee Procedures	Surgical	0.92	0.39		Z64B	Other Factors Influencing Health Status Age<80	Medical	0.34	0.35

	I19Z	Other Elbow or Forearm Procedures	Surgical	1.52	0.91		Z65Z	Multiple Other and Unspecified Congenital Anomalies	Medical	0.63	0.58
	I20Z	Foot Procedures	Surgical	1.20	0.91						

Appendix E: Ethics Approval from Victoria University[91]

VICTORIA UNIVERSITY
MELBOURNE AUSTRALIA

MEMO

TO Assoc Prof Liza Heslop
College of Health and Biomedicine
St Albans Campus
Victoria University

DATE 24/02/2015

FROM Associate Professor Deborah Zion
Chair
Victoria University Human Research Ethics Committee

SUBJECT Ethics Application – HREC Approved Application External to Victoria University

Dear Assoc Prof Heslop,

Thank you for submitting this request for ethical approval of the project entitled:

LRR13/PH/26: ***" Exploring associations between coded hospital workload indicators and adverse events: A proof of concept"***

The proposed research project has been accepted and deemed to meet the requirements of the National Health and Medical Research Council (NHMRC) 'National Statement on Ethical Conduct in Human Research (2007)' by the Chair of the Victoria University Human Research Ethics Committee. Approval has been granted from **24 February 2015 to 24 February 2017**. Any variations to the protocol must be approved through the original approving HREC and notified to VUHREC.

Please note that the Human Research Ethics Committee must be informed of the following: any changes to the approved research protocol, project timelines, any serious events or adverse and/or unforeseen events that may affect continued ethical acceptability of the project. In these unlikely events, researchers must immediately cease all data collection until the Committee has approved the changes. Researchers are also reminded of the need to notify the approving HREC of changes to personnel in research projects via a request for a minor amendment. It should also be noted that it is the Chief Investigators' responsibility to ensure the research project is conducted in line with the recommendations outlined in the National Health and Medical Research Council (NHMRC) 'National Statement on Ethical Conduct in Human Research (2007).'

On behalf of the Committee, I wish you all the best for the conduct of the project.

Kind regards,

Associate Professor Deborah Zion
Chair
Victoria University Human Research Ethics Committee

[91] The name of participating hospital has been omitted from this document to comply with the hospital ethical considerations.

Appendix F: Implementation of Exhaustive Search in SPSS

```
/*
 * *
 * Copyright (c) 2015-2017 Mahdi Bazargani
 *
 * The permission is granted for using of any section of this code for research purposes.
 *
*/

package spss;

import com.ibm.statistics.plugin.StatsUtil;
import java.io.ByteArrayOutputStream;
import java.io.FileNotFoundException;
import java.io.IOException;
import java.io.PrintStream;
import java.io.PrintWriter;
import java.util.TreeMap;
import java.util.ArrayList;
import java.util.List;
import java.util.regex.Matcher;
import java.util.regex.Pattern;


public class SPSSJavaPlugin {

    /**
     * @param args the command line arguments
     */
    public static void main(String[] args) throws FileNotFoundException, IOException {
        // TODO code application logic here

        String[] arrayHWIs = {
```

```
   "D_Weekends", "D_Weekday", "D_Beforeafterweekends", "Age", "A_Casualty",
   "A_ReferalsfromLMO", "A_WaitingList",
   "A_OtherAcuteHosp", "A_Newborn", "A_PsychUnit", "add1", "bed1", "diss1",
   "pe1", "sex1"

};

ArrayList<String> HWIs = new ArrayList<String>();
for (String s : arrayHWIs) {
   HWIs.add(s);
}
TreeMap<Double, String> map = new TreeMap<Double, String>();
PowerSetIterable<String> powerSet
      = new PowerSetIterable<String>(HWIs);
int count=0;
for (List<String> subset : powerSet) {
   String set = "";
   for (String s : subset) {
      set = set + s + " ";

   }
   if (subset.size() == 0) {
      continue;
   }
   String ma1 = "";

   System.out.println(String.valueOf(count));
   count++;

   try {
      StatsUtil.start();
      String[] command = {
         "GET ",
         "FILE='X:/chapter1/patientanalysis10.sav'. ",
```

```
    "OMS SELECT TABLES ",
    "/IF COMMANDS=['Generalized Linear Models'] SUBTYPES=['Goodness of Fit'] ",
    "/DESTINATION FORMAT=OXML XMLWORKSPACE='Goodness_of_Fit' ",
    "/TAG='fit'. ",
    "DATASET NAME DataSet1 WINDOW=FRONT.",
    "GENLIN TrueAdverseEvents (ORDER=ASCENDING) WITH  " + set,
    " /MODEL " + set,
    " DISTRIBUTION=MULTINOMIAL LINK=CUMLOGIT ",
    "/CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100 MAXSTEPHALVING=5 ",
    "PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012 ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD ",
    "LIKELIHOOD=FULL ",
    "/MISSING CLASSMISSING=EXCLUDE ",
    "/PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION. "

  };

  java.io.ByteArrayOutputStream outputStream = new ByteArrayOutputStream();
  PrintStream co = new PrintStream(outputStream);

  System.setOut(co);
  StatsUtil.submit(command);
  StatsUtil.stop();
  co.flush();
  co.close();

  String s = outputStream.toString("UTF-8");
  Pattern p = Pattern.compile("AIC\\)\\|(\\d+\\.\\d+)");
  Matcher m = p.matcher(s);
  boolean b = m.find();
```

```
            ma1 = m.group(1);
        } catch (Exception ex) {
            continue;
        }
        Double d = Double.valueOf(ma1);
        if (map.containsKey(d) && map.lastEntry().getKey() == d) {
            if (set.length() < map.lastEntry().getValue().length()) {
                map.remove(d);
                map.put(d, set);
            }
        } else {
            map.put(d, set);
        }

    }
    System.out.println("The set " + map.lastEntry().getValue() + "has the highest accuracy,
        AIC: " + map.lastEntry().getKey().toString());
    PrintWriter writer = new PrintWriter("X:/chapter1/output.txt", "UTF-8");
    writer.println("The set " + map.lastEntry().getValue() + "has the highest accuracy, AIC:
        " + map.lastEntry().getKey().toString());
    writer.close();

  }

}
/*
 * www.javagl.de - Utilities - Combinatorics
 *
 * Copyright (c) 2008-2013 Marco Hutter - http://www.javagl.de
 *
 *
*/
package spss;
```

```
import java.util.ArrayList;
import java.util.Iterator;
import java.util.List;
import java.util.NoSuchElementException;


public final class PowerSetIterable<T> implements Iterable<List<T>>
{
   /**
    * The input elements
    */
   private final List<T> input;

   /**
    * The total number of elements that the iterator will provide
    */
   private final int numElements;

   /**
    * Creates a new iterable over all elements of the power set
    * of the given elements
    *
    * @param input The input elements
    */
   public PowerSetIterable(List<T> input)
   {
      this.input = input;
      numElements = 1 << input.size();
   }

   public Iterator<List<T>> iterator()
   {
      return new Iterator<List<T>>()
```

```
{
   /**
    * The current index in the power set
    */
   private int current = 0;

   public boolean hasNext()
   {
      return current < numElements;
   }

   public List<T> next()
   {
      if (!hasNext())
      {
         throw new NoSuchElementException("No more elements");
      }

      List<T> element = new ArrayList<T>();

      // Insert into the current power set element
      // all elements of the input set that are at
      // indices where the current counter value
      // has a '1' in its binary representation
      for (int i = 0; i < input.size(); i++)
      {
         long b = 1 << i;
         if ((current & b) != 0)
         {
            element.add(input.get(i));
         }
      }
      current++;
      return element;
```

```
        }

        @Override
        public void remove()
        {
           throw new UnsupportedOperationException(
              "May not remove elements from a power set");
        }
      };
   }
}
```

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