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# USING LINKED HOSPITALISATION DATA TO DETECT NURSING SENSITIVE OUTCOMES: A RETROSPECTIVE COHORT STUDY

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## ABSTRACT

*Background:* Nursing sensitive outcomes are adverse patient health outcomes that have been shown to be associated with nursing care. Researchers have developed specific algorithms to identify nursing sensitive outcomes using administrative data sources, although contention still surrounds the ability to adjust for pre-existing conditions. Existing nursing sensitive outcome detection methods could be improved by using look-back periods that incorporate relevant health information from patient's previous hospitalisations.

*Design and setting:* Retrospective cohort study at three tertiary metropolitan hospitals in Perth, Western Australia.

*Objectives:* The objective of this research was to explore the effect of using linked hospitalisation data on estimated incidence rates of eleven adverse nursing sensitive outcomes by retrospectively extending the timeframe during which relevant patient disease information may be identified. The research also explored whether patient demographics and/or the characteristics of their hospitalisations were associated with nursing sensitive outcomes.

*Results:* During the five year study period there were 356,948 hospitalisation episodes involving 189,240 patients for a total of 2,493,654 inpatient days at the three tertiary metropolitan hospitals. There was a reduction in estimated rates for all nursing sensitive outcomes when a look-back period was applied to identify relevant health information from earlier hospitalisations within the preceding two years. Survival analysis demonstrates that the majority of relevant patient disease information is identified within approximately two years of the baseline nursing sensitive outcomes hospitalisation. Compared to patients without, patients with nursing sensitive outcomes were significantly more likely to be older (70 versus 58 years), female, have Charlson

comorbidities, be direct transfers from another hospital, have a longer inpatient stay and spend time in intensive care units ( $p \leq 0.001$ ).

*Conclusions:* The results of this research suggest that nursing sensitive outcome rates may be over-estimated using current detection methods. Linked hospitalisation data enables the use of look-back periods to identify clinically relevant diagnosis codes recorded prior to the hospitalisation in which a nursing sensitive outcome is detected. Using linked hospitalisation data to incorporate look-back periods offers an opportunity to increase the accuracy of nursing sensitive outcome detection when using administrative data sources.

*Keywords:* Care, Nursing; Hospitalisation; Medical Record Linkage; Nursing Methodology Research; Outcome Assessment (Health Care); Quality Indicators, Health Care

#### WHAT IS ALREADY KNOWN ABOUT THE TOPIC?

- Researchers have developed specific algorithms which use disease codes in administrative hospital data to identify when nursing sensitive outcomes may have occurred.
- This algorithmic method uses data sources in which multiple hospitalisations for the same individual on different occasions are not linked together.
- Existing chronic or long term medical conditions that affect nursing sensitive outcome risk are not always recorded in the same hospitalisation as a nursing sensitive outcome is detected.

#### WHAT THE PAPER ADDS

- Using linked hospitalisation data to incorporate look-back periods offers an opportunity to increase the accuracy of nursing sensitive outcome detection when using administrative data sources.
- Nursing sensitive outcomes rates may be over-estimated using current detection methods.

## BACKGROUND

### *Introducing nursing sensitive outcomes*

In recent decades an international body of literature has emerged addressing the need to quantify the contribution of nursing to quality health care (Aiken, Clarke, Sloane, Sochalski, & Silber, 2002; Duffield et al., 2007; Flood & Diers, 1988; Griffiths, Jones, Maben, & Murrells, 2008; Halloran, 1983; Kane, Shamliyan, Mueller, Duval, & Wilt, 2007; McCloskey & Diers, 2005; Needleman, Buerhaus, Mattke, Stewart, & Zelevinsky, 2001; Twigg, Duffield, Bremner, Rapley, & Finn, 2011). Nursing sensitive outcomes (NSOs) have been developed, which are specific patient health outcomes that have been shown to be associated with the quality and/or quantity of nursing care (Maas, Johnson, & Moorhead, 1996). There is a recognised need for NSOs that reflect positive outcomes of high quality and/or adequate quantities of nursing care delivery, but adverse outcomes are often used due to the challenges of data collection, generalizability, and outcome measurement (Griffiths, et al., 2008; Savitz, Jones, & Bernard, 2005). Eleven adverse outcomes, referred to as NSOs, were used in this study: central nervous system complications, surgical wound infection, pulmonary failure, urinary tract infection (UTI), pressure ulcer, hospital acquired pneumonia, deep vein thrombosis, upper gastrointestinal bleeding, sepsis, physiologic or metabolic derangement, and shock or myocardial infarction (Griffiths, et al., 2008; Kane, et al., 2007; Van den Heede, Clarke, Sermeus, Vleugels, & Aiken, 2007).

### *The use of administrative data in determining NSOs*

Hospital morbidity data from administrative sources have been utilised to identify and quantify NSOs as they afford the large sample size required for statistical analyses of these relatively rare occurrences. Hospital morbidity data are derived from inpatient discharge summaries and contain demographic characteristics and International Classification of Disease (ICD) codes which represent medical conditions and procedures experienced by individuals during inpatient hospitalisations (National Center for Health Statistics, 1991; National Centre for Classification in Health, 2008; Zhan & Miller, 2003). ICD codes from hospital morbidity data are used to identify NSOs that occur during an inpatient stay; this is explained in greater detail below. Validation studies have reported high accuracy levels in the diagnosis coding of the Western Australian hospital morbidity data (Mnatzaganian, Ryan, Norman, & Hiller, 2012; Teng, Finn, Hung, Geelhoed, & Hobbs, 2008). Adding to their feasibility for use in NSO detection, administrative data sources are usually accessible for

research purposes, cost-effective to access and collected over time in a reasonably uniform format (Mitchell et al., 1994; Virnig & McBean, 2001).

Two disadvantages associated with using hospital morbidity data to identify NSOs are: firstly, in addition to nursing care quality, patient outcomes are influenced by the underlying health status of the patient and other factors (i.e. hospital characteristics including number of beds, metropolitan or non-metropolitan location, teaching status) (Griffiths, et al., 2008; Irvine, Sidani, & Hall, 1998; Kane, et al., 2007); and secondly, hospital morbidity data does not typically distinguish whether a particular condition was present prior to hospitalisation and thus a comorbidity, or whether it was a complication that developed during hospitalisation (Iezzoni et al., 1994; Lawthers et al., 2000; Miller, Elixhauser, Zhan, & Meyer, 2001; Zhan & Miller, 2003). Researchers have aimed to resolve the first of these disadvantages by statistically adjusting for patient characteristics and other factors (Aiken, et al., 2002; Needleman, et al., 2001). Without access to a reliable present on admission indicator (POA, described below), the second disadvantage has been addressed by designing specific algorithms to classify as NSOs only those cases which were avoidable inpatient complications and not attributable to the patient's underlying health status (Iezzoni, et al., 1994; Miller, et al., 2001; Needleman, et al., 2001).

#### *NSO identification algorithms*

Researchers have developed specific algorithms for each NSO which use ICD codes in the hospital morbidity data to identify when NSOs may have occurred (Iezzoni, et al., 1994; Needleman, et al., 2001). The NSO algorithms use a combination of inclusion and exclusion criteria to ensure only conditions that cannot be explained by the patient's underlying health status are counted as NSOs. For example, when an ICD code for pressure ulcer is found, the event is only counted as an NSO in the absence of a code for paralysis, since paralysis increases the patient's risk of pressure ulcer independently of the nursing care administered. This method was designed to enhance the specificity of NSO identification even though researchers only had access to data sources in which each hospitalisation is recorded as a discrete event (i.e. multiple hospitalisations for the same individual on different occasions are not linked together) (Needleman, et al., 2001). Accurate NSO identification using this unlinked method relies on the assumption that all conditions that affect a patient's risk of NSO occurrence will be recorded in the discharge summary for the same hospitalisation during which the NSO is documented. However, it has been found that existing chronic or long term medical conditions that affect NSO risk are not always recorded in the same hospitalisation as an NSO is detected (Wilson, Bremner, Hauck, &

Finn, 2012). Stable diagnoses (e.g. paraplegia occurring in the past) may not be recorded in the discharge summary or coded into the hospital morbidity data every time a person is an inpatient if they did not specifically contribute to that hospitalisation, even though they may still influence NSO risk. Using linked hospitalisation data to apply look-back periods to NSO detection algorithms is one way to address this problem. Linked hospitalisation data and look back periods are explained below.

#### *Linked hospitalisation data*

Data linkage refers to “the bringing together in a single file, of records derived from different sources, but relating to the same individual” (Hobbs & McCall, 1970, p. 375). Whereas hospital morbidity data normally consist of standalone records for each hospitalisation, linked hospitalisation data identify when different hospitalisation records refer to the same individual over time and at different hospitals. Every time a person is hospitalised, the record of that event in the hospital morbidity data is linked to form a chain of person-specific hospitalisation records. NSO identification accuracy could be improved by taking advantage of linked hospitalisation data to include all relevant diagnoses from a patient’s chain of hospitalisations. This would build on existing NSO detection methods by using look-back periods that incorporate previous hospitalisations in the patient’s chain into established NSO identification algorithms, thus extending the period during which relevant exclusion codes are identified. Holman, Bass, Rouse, and Hobbs (1999) detail the probabilistic matching methods used by the Western Australian Data Linkage Branch (WADLB), a body within the state’s Department of Health, to construct master linkage keys linking hospital morbidity data. The validity of the linkages (i.e. whether the linked hospitalisations do in fact refer to the same individuals over time) has been tested and an error rate of 0.11% was reported, including missed links and incorrect matches (Holman, et al., 1999). Master linkage keys are maintained over time and any errors detected are reported to the WADLB, thus continuously maintaining the linkage quality (Holman et al., 2008).

#### *Look-back periods*

Look-back periods identify diagnosis codes recorded during all identified past hospitalisations for each patient (Zhang, Iwashyna, & Christakis, 1999). With look-back periods, an adverse event is labelled an NSO based on the ICD codes detected during a certain period of time as opposed to only those detected during a single hospitalisation. When an adverse outcome is detected, previous hospitalisations for that patient within the look-

back period are taken into account when deciding whether the adverse outcome should be attributed to nursing care or the patient's underlying health status. Using look-back periods to identify relevant ICD codes in a patient's hospitalisation history has the potential to contribute to more accurate NSO detection in two ways. Firstly, by enabling the detection of clinically relevant exclusion codes that are not recorded during the same hospitalisation as the NSO. For example, if a person meets the criteria for pressure ulcer during a 2005 hospitalisation but had a code for paraplegia (i.e. an exclusion code in the pressure ulcer NSO algorithm) recorded during a hospitalisation in 2003, the pressure ulcer may be attributed to the patient's underlying health status (paraplegia) and therefore not counted as an NSO. Secondly, by ensuring an NSO is not counted repeatedly for a person who had multiple hospitalisations within a short time. For example, if a pressure ulcer is recorded for the same person during two hospitalisations only five days apart, it is probable the codes do not represent two clinically independent events. This study used NSO-specific look-back periods so that only disease codes relevant to that particular NSO were considered relevant when applying the look-back period. For example, previous hospitalisations including pneumonia NSO were not considered relevant to a hospitalisation where UTI NSO was detected.

The look-back method applied in the study builds on other work in the field which has included inpatient data from previous hospitalisations for the same person. Sales, et al. (2008) did not attribute adverse outcomes to nursing care if a patient had the same complication more than once in 12 months. This study expands their work by exploring the timeframe that should be used to look back for the same NSO and for other disease codes already established as relevant in algorithms routinely used to identify NSOs. Other attempts to improve differentiation between hospital acquired and present on admission (POA) adverse outcomes recorded in administrative hospital data have been reported in the literature (Mark & Harless, 2010). Though this indicator is useful for indicating whether an NSO was POA, look-back periods also capture exclusion codes that may not be documented on the same hospitalisation record, even though they are relevant to whether the adverse outcomes should be classified as NSOs (Wilson, et al., 2012). In addition, POA indicator reliability is still being established in administrative data sources in which it is available (Bahl, Thompson, Kau, Hu, & Campbell Jr, 2008; Hughes et al., 2006; Jackson, Duckett, Shephard, & Baxter, 2006; Naessens, Campbell, Berg, Williams, & Culbertson, 2007).

## AIM

The aim of this research was to explore how NSO rates are affected when linked hospitalisation data are used to capture relevant ICD codes recorded in a patient's hospitalisation history compared to algorithms that use only a single hospitalisation record. The specific research questions investigated were: does using linked hospitalisation data to incorporate look-back periods into NSO detection algorithms

1. identify relevant exclusion codes recorded during previous hospitalisations,
2. detect when a patient has the same NSO recorded on multiple hospitalisations, or
3. have an effect on NSO rates?

The research also explored whether patient demographics and/or the characteristics of their hospitalisations were associated with NSOs.

## METHODS

### *Study design and population*

A retrospective cohort study design was used to address the research questions. The cohort comprised adult inpatient hospitalisation episodes at three tertiary metropolitan hospitals in WA between 1 January 2004 and 31 December 2008. Patients were considered adults if they were 18 years or older at the time of admission to hospital. Inpatient hospitalisations were defined as those including at least an overnight stay. Data used in the analysis were extracted in two stages from the Hospital Morbidity Data Set and Mortality Data Set by the WADLB. In the first stage all hospitalisations meeting the cohort criteria were extracted. Following this, mortality data and the chains of all previous hospitalisations were extracted for all patients with a hospitalisation identified during the first stage. Look-back period analysis incorporated data from the second stage of extraction to identify when relevant ICD codes were recorded earlier in a patient hospitalisation chain. Linked mortality data were used to identify when death occurred within 30 days of a hospital admission, including when the death did not occur in hospital. Hospitalisation chains extracted in the second stage were drawn from data at all WA hospitals since 1 July 1999. Ethics approval for this study was granted by the Human Research Ethics



Committees of The University of Western Australia (reference: RA/4/1/2469) and the Government of Western Australia Department of Health (Project #2009/56).

## *Measures*

### *Measure of NSOs*

The outcomes of interest, NSOs, were identified using an inclusion and exclusion criteria algorithm based on the presence and/or absence of particular disease codes (using the ICD 9<sup>th</sup> and 10<sup>th</sup> revisions (National Center for Health Statistics, 1991; National Centre for Classification in Health, 2008)). The algorithms used to identify NSOs in this study were first developed and published by Needleman, et al. (2001) using ICD-9 disease codes that were subsequently mapped to ICD-10 (McCloskey & Diers, 2005), and have been used to identify NSOs in a WA inpatient population (Twigg, et al., 2011). For an NSO to be detected when no look-back period was applied a hospitalisation record had to contain an NSO inclusion code for the specific NSO and have none of the exclusion codes for that same NSO. Rates calculated based on NSO detection where no look-back period was applied are referred to throughout the paper as baseline NSO rates. Look-back periods were then applied to adjust the baseline NSO rates, no longer counting patients who had had the same NSO or that NSOs exclusion codes within the look-back period timeframe. For each hospitalisation record where a baseline NSO was identified, linked hospitalisation records for that patient were examined to determine the number of days since their last hospitalisation with recorded ICD codes that were relevant to the baseline NSO. For an NSO to be detected when a look-back period was applied a hospitalisation record had to contain an NSO inclusion code for the specific NSO and that patient had to have no hospitalisations during look-back with same NSO or its exclusion codes. NSO rates per 1,000 inpatient days were calculated as per the formula in Figure 1.

*Figure 1: NSO rate per 1,000 patient days equation.*

$$\text{NSO per 1,000 patient days} = \frac{\text{NSO frequency}}{\text{total patient days during study period}} \times 1,000$$

*Applying look-back periods to the measure of NSOs using linked hospitalisation data*

It is possible to employ look-back periods by taking advantage of the longitudinal, population level, individually linked inpatient and mortality data available through the WADLB. Individual NSO algorithms were treated separately when the look-back period was applied and only ICD codes already part that NSOs detection algorithm were considered in the look-back (i.e. when a sepsis NSO was detected, only codes already in the NSO detection algorithm for sepsis were searched for during look-back). The cut-off for look-back was 1 July 1999, thus the maximum possible look-back was 1,645 days for those at the beginning of the study period and 3,470 days for those at the end.

### *Charlson Comorbidity Score*

The Charlson Comorbidity Score (CCS) is a weighted score that takes into account the number and severity of comorbid diseases an individual has recorded in their hospitalisation history (Charlson, Pompei, Ales, & MacKenzie, 1987). In this study the CCS was used as a descriptive characteristic to compare the comorbid conditions of those with and without NSOs. CCS was calculated using a combination of the Deyo, Cherkin and Ciol (1992) and Quan, Sundararajan, Halfon, et al. (2005) methods.

### *Analysis*

Analysis was done using IBM SPSS Statistics Version 21 (IBM SPSS Inc. 2010, Chicago, IL, [www.spss.com](http://www.spss.com)). Demographic data were summarised using means, standard deviations and proportions as appropriate. T-tests and chi-squared tests were used to compare differences in demographic data between those with and without NSOs. NSO rates were calculated per 1,000 inpatient days (Figure 1). Survival analysis was conducted to support look-back period length. Assessing each NSO individually, the survival analysis shows the proportion of those with a baseline NSO who have hospitalisations with ICD codes relevant to that NSO recorded during the days of look-back. Two survival functions were plotted for each NSO, one to show the days since the NSOs exclusion codes were last recorded and the other to show the number of days since the same NSO was last recorded. Proportional changes in NSO rates adjusted to include a two year look-back period were compared to the baseline NSO rates.

## RESULTS

During the five year study period there were 356,948 hospitalisation episodes involving 189,240 patients for a total of 2,493,654 inpatient days at the three tertiary metropolitan hospitals in Perth. Table 1 contains a comparison of demographic characteristics for hospitalisation episodes in which no NSOs were documented and those in which one or more NSOs were documented. Using NSO detection algorithms for identifying baseline NSOs (i.e. not including any look-back component), one or more NSOs were recorded during approximately 18% (n=64,258) of hospitalisation episodes in the study period. Individuals who experienced an NSO during a hospitalisation were on average 12 years older and more likely to be female (53% versus 45%,  $p<0.001$ ). Three quarters of hospitalisations with baseline NSOs also had one or more of the Charlson comorbidities ( $CCS\geq 1$ ) documented in the previous five years. The proportion of hospitalisations with one or more Charlson comorbidities in the previous five years was significantly higher among those with baseline NSOs (75% versus 46%,  $p<0.001$ ).

Table 1 also details descriptive characteristics of the hospitalisation episodes and shows the differences between hospitalisations with and without documented baseline NSOs. Compared with those for which an NSO was not recorded, hospitalisations with an NSO were significantly more likely to be preceded by time spent in another acute hospital or other care facility (35% versus 21%,  $p<0.001$ ) and were more likely to be an emergency admission (80% versus 74%,  $p<0.001$ ). Average length of stay was 7.7 days longer for hospitalisations in which an NSO was recorded compared to those with no NSOs documented ( $p<0.001$ ). Hospitalisations with one or more NSOs recorded were four times more likely to include time spent in the Intensive Care Unit (ICU; 12% versus 3%,  $p<0.001$ ) and time spent in the ICU was longer as a proportion of total length of stay (39% versus 23%,  $p<0.001$ ). Only 7% of hospitalisations with NSOs recorded did not have any previous hospitalisations during the look-back period.

Table 1: Descriptive characteristics of the hospitalisation episodes

|   | Hospitalisations with no baseline NSOs <sup>1</sup> recorded | Hospitalisations with one or more baseline NSOs <sup>1</sup> recorded |
|---|--|---|
| Hospitalisation episodes, n   | 292,690  | 64,258  |
| Age, mean (SD)  | <b>58.0</b> (20.7)   | <b>70.0</b> (18.6)  |
| Sex, %  |  |   |
| Male  | <b>55</b>  | <b>47</b>   |
| Female  | <b>45</b>  | <b>53</b>   |
| Proportion of hospitalisation with a CCS <sup>2</sup> ≥1 (based on previous 5 years), %   | <b>46</b>  | <b>75</b>   |
| Source of referral, %   |  |   |
| Home  | <b>79</b>  | <b>65</b>   |
| Other acute hospital  | <b>18</b>  | <b>27</b>   |
| Other <sup>3</sup>  | <b>3</b>   | <b>8</b>  |
| Hospitalisation type, %   |  |   |
| Emergency   | <b>74</b>  | <b>80</b>   |
| Elective  | <b>26</b>  | <b>20</b>   |
| Length of stay in days, mean (SD)   | <b>5.6</b> (8.4)   | <b>13.3</b> (17.0)  |
| Proportion of hospitalisations including time spent in ICU, %   | <b>3</b> <sup>4</sup>  | <b>12</b> <sup>5</sup>  |
| Percentage of length of stay in ICU, IF time was spent there, mean % (SD)   | <b>23</b> (21)   | <b>39</b> (31)  |
| Proportion of hospitalisations during the study period with no other hospitalisations during the look-back period, %  | <b>14</b>  | <b>7</b>  |
| NB: bold typeface indicates statistically significant difference of p≤0.001 comparing values for hospitalisations with no NSOs recorded and hospitalisations with one or more NSOs recorded |  |   |
| 1. Baseline NSOs (i.e. not including the look-back component for identifying exclusion codes)   |  |   |
| 2. Charlson Comorbidity Score   |  |   |
| 3. Other referral sources included residential aged care facility, prison, psychiatric hospital and unspecified source  |  |   |
| 4. ICU data was incomplete therefore this is a proportion of 289,384 (missing data is less than 1.13% of sample)  |  |   |
| 5. ICU data was incomplete therefore this is a proportion of 63,862 (missing data is less than 0.62% of sample)   |  |   |

Survival curves were plotted to depict the proportion of individuals with each baseline NSO that had a disease code relevant to that NSO (y-axis) over the days of look-back (x-axis). The curves for all NSOs followed a similar pattern so the curves for UTI are described in detail as an example (Figure 2). In Figure 2 (a), over the maximum look-back length of 3,470 days, approximately 33% (1.0 minus the point at which the curve tails off, 0.67) of those with a baseline UTI NSO had previous hospitalisations with a UTI exclusion code. Similarly, approximately 40% had another UTI NSO detected within the maximum look-back (Figure 2 (b)). As demonstrated by the UTI examples in Figure 2, survival curves for all NSOs declined steeply in the early part of the look-back and levelled out as the maximum look-back was reached.

Figure 2: Survival curves for the proportion of baseline UTI NSOs for which there are hospitalisations with relevant ICD codes during the look-back period (UTI baseline N=15,458).

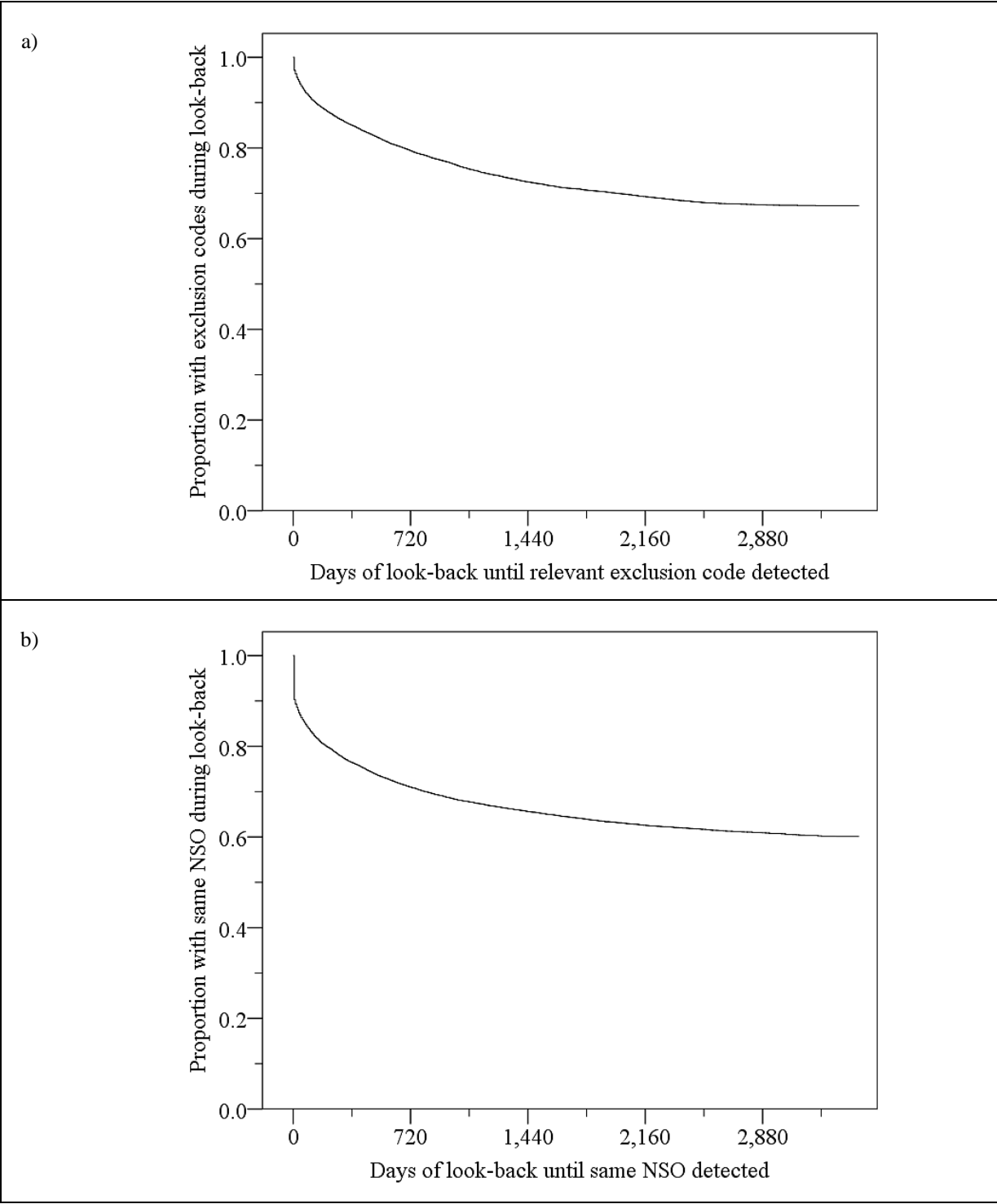


Table 2 shows the number of days of look-back it took for 75% of relevant codes to be detected for each NSO and the rate of each NSO per 1,000 inpatient days with no look-back period incorporated (i.e. the baseline NSO)

compared to the NSO rates per 1,000 inpatient days calculated with a 2 year (730 days) look-back period.

Including a look-back period causes a reduction in NSO rate compared to the baseline rate for all NSOs.

*Table 2: Days of look-back to find 75% of relevant disease codes for each NSO and NSO rates (95% confidence intervals) per 1,000 inpatient days at baseline and following application of a 2 year look-back period.*

| NSO                                  | Days of look-back taken to detect 75% of previous: |          | NSO rate (95% confidence interval): |                                |
|--------------------------------------|--|----------|-------------------------------------|--------------------------------|
|                                      | Exclusion codes for the same NSO                   | Same NSO | With no look-back period (baseline) | With a 2 year look-back period |
| Central nervous system complication  | 715  | 776      | 4.57 (4.48, 4.65)                   | 2.72 (2.66, 2.79)              |
| Wound infection                      | 2,094  | 1,071    | 1.47 (1.43, 1.52)                   | 1.24 (1.19, 1.28)              |
| Pulmonary failure                    | 316  | 1,702    | 1.09 (1.05, 1.13)                   | 0.61 (0.57, 0.64)              |
| Urinary tract infection              | 1,019  | 581      | 6.20 (6.10, 6.30)                   | 3.64 (3.57, 3.72)              |
| Pressure ulcer                       | 52   | 180      | 1.66 (1.61, 1.71)                   | 0.41 (0.38, 0.43)              |
| Pneumonia                            | 886  | 1,199    | 3.72 (3.64, 3.79)                   | 2.59 (2.53, 2.66)              |
| Deep vein thrombosis                 | 1,278  | 184      | 0.91 (0.87, 0.94)                   | 0.67 (0.64, 0.70)              |
| Upper gastrointestinal tract bleed   | 431  | 1,897    | 0.89 (0.86, 0.93)                   | 0.50 (0.47, 0.53)              |
| Sepsis                               | 27   | 1,124    | 1.58 (1.53, 1.63)                   | 0.42 (0.40, 0.45)              |
| Physiologic or metabolic derangement | 1,470  | 911      | 7.28 (7.17, 7.38)                   | 5.03 (4.94, 5.12)              |
| Shock or myocardial infarction       | 205  | 2,378    | 0.46 (0.43, 0.49)                   | 0.23 (0.21, 0.25)              |

## DISCUSSION

The primary aim of this study was to use linked hospitalisation records to investigate the impact on NSO rates of applying look-back periods to NSO detection algorithms. When using administrative data to identify NSOs, researchers incorporated exclusion criteria into identification algorithms in an effort to accurately classify adverse events as nursing sensitive only when they could not be attributed to prior events or patients' pre-existing conditions (Needleman, et al., 2001). The underlying assumption of this study is that though an adverse event during one hospitalisation is attributed to nursing care (i.e. labelled an NSO), there may be information recorded during earlier hospitalisations for the same person which clarify that it is more appropriate to attribute the adverse event to the patient's underlying health status.

The results of this study indicate that the majority of disease codes relevant to whether an adverse event during a hospitalisation should be attributed to nursing care are detected within two years. Combining a two year look-back period with existing NSO detection algorithms resulted in a significant reduction of all 11 NSO rates

estimated. This is consistent with the recent research finding that pre-existing events or conditions relevant to NSO identification are not always coded in the hospitalisation during which an NSO is detected (Wilson, et al., 2012). If all relevant pre-existing events or conditions experienced by a patient were always coded during every hospitalisation, a proportion of adverse outcomes attributed to nursing care would be instead ascribed to the underlying health status of the patient. With due consideration of clinically appropriate look-back period timeframes, retrospectively extending the period during which relevant exclusion criteria are detected represents an improvement in the accuracy of NSO identification.

The characteristics of hospitalisations during which NSOs were recorded were significantly different from those without; older patients and those with additional comorbid conditions more commonly experienced NSOs. There was greater complexity to hospitalisations with one or more NSOs identified; they were significantly more likely to start as a transfer from another care facility, have a longer inpatient period, include time in an ICU and include a relatively greater proportion of time in ICU. The relationship between hospitalisation complexity and NSOs warrants further explication. In some cases greater hospitalisation complexity may be a precursor to increased risk of NSOs whereas in other cases greater complexity of care may be required as a result of an NSO having developed. Clearer understanding of this relationship could help to identify individuals at higher risk of experiencing an NSO so that their care can be tailored to prevent these complications, for example by implementing specific NSO prevention care plan pathways.

This research demonstrates that incorporating look-back periods into NSO detection algorithms results in a reduction in estimated NSO rates. The types of codes in the exclusion criteria algorithms for different NSOs may be related to variations in rate reduction between NSOs. Rates of wound infection and deep vein thrombosis were least affected with overall reductions of 16% and 26%, respectively. The NSO algorithm for wound infection excludes only those with a primary diagnosis of wound infection and the deep vein thrombosis NSO algorithm excludes those with a primary diagnosis of pregnancy or deep vein thrombosis. The smaller impact of look-back periods on these NSO rates may be related to the limited exclusion criteria in the baseline detection algorithms. Pressure ulcer and sepsis had the largest reductions (75% and 73% respectively). Among the exclusion criteria for the pressure ulcer NSO algorithm are those with a primary diagnosis of pressure ulcer or a diagnosis of hemiplegia, quadriplegia or paraplegia. Similarly, the sepsis NSO algorithm excludes those with a primary diagnosis of sepsis or a diagnosis indicating an immunocompromised state (e.g. acquired immune deficiency syndrome). In both of these NSOs, broader exclusion criteria included chronic conditions (paralysis

and compromised immune system) that would impact on a patient's NSO risk even if they were recorded during an earlier hospitalisation. Extending the period of look-back from two years to include all hospitalisations may be clinically relevant when the exclusion codes for an NSO include chronic conditions such as paralysis or diabetes which are often permanent afflictions. Many relevant exclusion codes are captured within two years and the clinical relevance and feasibility of linking data for longer look-back periods must be weighed against the additional benefit of doing so.

The most appropriate look-back period for each NSO should take into consideration the pathophysiology underpinning the NSO and the type of exclusion criteria. Disease codes should only be included from previous hospitalisations if they are still clinically relevant to the hospitalisation during which the NSO is identified. Pressure ulcers are an example of an NSO where the application of a longer look-back period may be appropriate. A pressure ulcer NSO is counted using Needleman, et al.'s (2001) algorithm when a hospitalisation has a pressure ulcer disease code recorded *unless* it is the primary disease code (i.e. the primary reason they were hospitalised) or there is also a disease code for paralysis. Although paralysis places an individual at higher risk of suffering a pressure ulcer independently of the quality of nursing care he or she receives it may not be coded for in the hospitalisation during which the pressure ulcer NSO is documented, 75% of paralysis codes are detected in the first 52 days of look-back (Table 2). A look-back period would enable detection of relevant paralysis disease codes occurring earlier in the patient's hospitalisation history. Including a look-back period will increase the likelihood that all disease codes relevant to NSO identification are detected.

Limited use of look-back periods in the literature to date may mean that NSO rates calculated using administrative data have been over-estimated. Because other hospitalisations are not normally included in algorithms that detect NSOs, the current implicit assumption is that previous hospitalisations, even if they only occurred within the preceding month, have no bearing on the NSO event. In this study two year look-back periods were used in an effort to accurately adjust for patient's underlying health status as this timeframe captured the majority of relevant hospitalisation history for patients with baseline NSOs. Detection algorithms that have been constructed to identify NSOs in administrative data should be revisited in the context of the availability of linked hospitalisation data.

Access to linked hospitalisation data in this study made it possible to use look-back periods to calculate the rates of NSOs in a large cohort of hospitalisations across three teaching hospitals. Linked hospitalisation data may be



used to gain other useful insights in the study of NSOs. In this study the hospitalisations of 27% of patients with a baseline NSO documented began as transfers from other acute care hospitals, compared with 18% of those without NSOs identified. Linked hospitalisation data could be used to explore the burden of NSO occurrence to the health care system; whether individuals are transferred because of the NSO or due to deterioration in their condition, and whether the interruption to their continuity of care has an impact on health outcomes. Linked hospitalisation data could also be used to explore the burden individuals who suffer multiple NSOs over time place on the health care system.

### *Limitations*

There are several limitations of the study. Present on admission (POA) indicators are increasingly used in administrative data internationally and these study results may not be generalizable to those contexts (Mark & Harless, 2010; Sales, et al., 2008). A POA indicator was not available in the data source used for this study. Although coding errors or code omissions are problems associated with using administrative data, high levels of accuracy have been reported in validation studies of the WA hospital morbidity data (Mnatzaganian, et al., 2012; Teng, et al., 2008). The scope of this study allowed for the comparison of characteristics of those with and without NSOs only when NSOs were detected using the baseline detection algorithm. Future studies should address whether differences in the characteristics of those with and without NSOs are preserved when NSOs are detected using look-back periods. Finally, look-back periods require linkage of all hospitalisation episodes in a patient's history to comprehensively identify all diagnosis codes that may be relevant to NSO detection. WA is geographically isolated, with a well-developed linked health data system. However, it is possible that not all hospitalisations for an individual were included in the data linkage system because it does not capture hospitals in other states of Australia or overseas.

### CONCLUSION

The results of this research suggest that NSO rates may be over-estimated using current detection methods. Detection algorithms were originally designed to try to restrict the identification of NSO cases to only those suffering complications which could not be attributed to their pre-existing health status. To date, research in this field has been circumscribed by access to non-linked hospital morbidity data which does not have the capacity to identify multiple hospitalisation records that relate to the same individual. Linked hospitalisation data enables the

use of look-back periods to identify clinically relevant diagnosis codes recorded prior to the hospitalisation in which an NSO is detected. Using linked hospitalisation data to incorporate look-back periods offers an opportunity to increase the accuracy of NSO detection when using administrative data sources. A look-back period of 2 years for relevant disease codes captures the majority of relevant disease codes for individuals who experience them.

Further exploration is needed to elucidate the most appropriate look-back period for each NSO. Whereas some NSO exclusion codes are relevant even if they were recorded years earlier, others are only relevant if recorded in close proximity to the NSO. Future investigation should take into consideration the disease process of each NSO and the types of codes included as exclusion criteria. Future research should explore whether incorporating look-back periods in NSO detection affects the relationship between NSO incidence and the quality and/or quantity of nursing care delivered.

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