# 4 Methods

## 4.1 Data

National hospital separations data were provided by the AIHW from the NHMD.
A separation is defined as: 'A formal or statistical process by which an episode of care for an admitted patient ceases' (AIHW 2005).

This report uses data for hospital separations that occurred in Australia during the 3 years from 1 July 2004 to 30 June 2007.

Data for the second year in this 3–year period were used for the single-year analysis.

Hospital separations in 2004–05 and 2005–06 were coded according to the 4th edition of ICD-10-AM (NCCH 2004). Those in 2006–06 were coded according to the 5th edition.

### 4.1.2 Peer groups

The hospital peer groups used in this report are according to the AIHW Peer Group Report Round 10 (2005–2006) AR-DRGv5.0. The groups and their designations are shown in Table 2.

We have not presented results for all peer groups. To do so would require a large number of tables and figures, not all of which are necessary for the purposes of this project.

**Table 2: AIHW Peer Groups**

| AIHW Peer Group | Designation | Definition |
|---|---|---|
| Principal referral and specialist women's and children's | A1 | Major city hospitals with >20,000 acute casemix-adjusted separations and Regional hospitals with >16,000 acute casemix-adjusted separations per annum |
| | A2 | Specialised acute WCHs with >10,000 acute casemix-adjusted separations per annum |
| Un-peered and other hospitals | A9 | Prison medical services, special circumstance hospitals, Major city hospitals with <2000 acute casemix-adjusted separations, hospitals with <200 separations, etc. |
| Large hospitals | B1 | Major city acute hospitals treating more than 10,000 acute casemix-adjusted separations per annum |
| | B2 | Regional acute hospitals treating >8,000 acute casemix-adjusted separations per annum, and remote hospitals with >5,000 casemix-adjusted separations |
| Medium hospitals | C1 | Medium acute hospitals in Regional and Major city areas treating between 5,000 and 10,000 acute casemix-adjusted separations per annum |
| | C2 | Medium acute hospitals in Regional and Major city areas treating between 2,000 and 5,000 acute casemix-adjusted separations per annum, and acute hospitals treating <2,000 casemix-adjusted separations per annum but with >2,000 separations per annum |
| Small acute hospitals | D1 | Small Regional acute hospitals (mainly small country town hospitals), acute hospitals treating <2,000 separations per annum, and with <40% non-acute and outlier patient days of total patient days |
| | D2 | Small non-acute hospitals, treating <2,000 separations per annum, and with >40% non-acute and outlier patient days of total patient days (D2) plus Multipurpose service (E2) – Small subacute and non-acute hospitals (G) |
| | D3 | Small remote hospitals (<5,000 acute casemix adjusted separations but not 'Multipurpose services' and not 'Small non-acute'. Most are <2,000 separations) |

*Note:* Excludes psychiatric hospitals. Definitions from Australian Hospital Statistics 2005–06 (AIHW 2007).

## 4.2   Single-year analysis: 2005–06

Rates of in-hospital mortality amongst Australian hospitals in 2005–06 were compared using indirect standardisation. Separate analyses were performed for three sets of cases:

1.  Diagnoses accounting for 80% of mortality: cases with one of the principal diagnosis codes listed in Appendix 1. These 68 codes are associated with the largest numbers of cases ending with in-hospital death in the subset of the 2005–06 NHMD file meeting our study criteria. This group accounts for 80% of deaths and about 20% of cases.

2.  Diagnoses accounting for the remaining 20% of mortality. This group includes cases with any Principal Diagnosis code that is not in Appendix 1.

3.  All diagnoses. This is the sum of the previous two groups, and includes 100% of in-scope cases and 100% of in-scope deaths.

## 4.3   Calculation of HSMRs

HSMRs were calculated for each hospital using the ratio of the observed to expected number of deaths:

$$\text{HSMR} = \frac{\text{Actual number of in-hospital deaths amongst selected diagnosis groups}}{\text{Expected number of in-hospital deaths amongst selected diagnosis groups}} \times 100$$

Logistic regression was used to calculate the expected number of deaths in each hospital. The 'standard' population was the combined population of all hospitals included in each analysis. Each HSMR was therefore a ratio of the observed hospital mortality rate to the rate for all hospitals combined based on patients with the same characteristics. The logistic regression model used for all principal analyses, referred to here as the RACM model, followed the approach of the CIHI (2007), which has also been used in the UK and Holland.

Hospital-specific expected numbers of deaths were calculated by summing the probabilities of death obtained from coefficients for the logistic regression model. The independent variables included in the RACM model are listed and described in Section 4.5.2.

As stated in Section 3.3.8, the HSMRs were recalibrated before presentation.

## 4.4   Graphical methods of presentation

Graphs were generated using Stata Statistical Software, Release 10.

### 4.4.1  Caterpillar plots

Caterpillar plots are simply graphical presentations of HSMRs from each institution within a population of interest. Each institution's HSMR is graphed from three points: the HSMR value and the upper and lower 95% confidence limits. The population average of 100 is provided by way of reference. The plots were generated with the relevant Stata commands.

## 4.4.2 Funnel plots

Funnel plots allow many points to be plotted simultaneously, with information about whether each point is significantly above or below the expected, or average, value. Funnel plots were developed as a method of displaying data for statistical process control (SPC). They avoid the ranking approach that some methods of displaying performance data use. The Association of Public Health Observatories of the UK (APHO) has adopted and adapted this method for a report on indicators of public health in the regions of England, and the APHO method for generating funnel plots was accessed at http://www.apho.org.uk/default.aspx (June 1 2008) and used here.

Creating a funnel plot requires the superposition of two charts:

1. A scatter plot of the expected number of deaths against the HSMR.

2. A scatter plot with interpolated lines of the SMR; that is, 100% and Poisson control limits around that measure. The '*invgammap*' function in STATA was used to determine the Poisson control limits.

The construction of the control limits depends on distribution of the underlying performance measure. The width of the limits is somewhat arbitrarily equivalent to 95% and 99.8% confidence intervals around the target value (roughly equivalent to two and three standard deviations). The three standard deviations measure is often taken as the boundary between 'common-cause' and 'special-cause' variation in control chart method.

# 4.5  Case selection

## 4.5.1 Inclusion/exclusion criteria

**Inclusion criteria**

- admission for acute care (episode type=1)

- age at admission from 0 to 120 years

- gender recorded as male or female (i.e. not 'missing')

- length of stay up to 365 consecutive days

- admission category: either elective or emergency

- Principal Diagnosis at discharge. The proportion of in-hospital deaths was calculated for the set of cases with each three-character ICD-10-AM code. Diagnosis codes were ranked in descending order of this proportion. Three sets of records were selected, each being used for part of the analysis:

    (i)   high risk: the set of records with three-character ICD-10-AM codes that ranked highest in terms of the diagnosis-specific number of deaths and which, together, account for 80% of all in-hospital deaths. (See Appendix 1.)

    (ii)  lower risk: the set with all other three-character ICD-10-AM codes

    (iii) all records satisfying the selection criteria. This is the sum of (i) and (ii).

**Exclusion criteria**

- patients discharged against medical advice (defined using AIHW data element 'mode of separation' = Left against medical advice/discharge at own risk)
- palliative care patients (recalibrated for single year HSMR production)
- neonates (infant age >0 and <= 28 days)

**Outcome**

- death in hospital was defined as Mode of Separation = died

## 4.5.2  The logistic regression model

The independent variables used for the RACM model used in all primary analyses were:

- age (in years at time of admission)
- sex (based on sex recorded at discharge)
- length of stay group (as six separate categories; i.e. 1 day, 2 days, 3–9 days, 10–15 days, 16–21 days and 22–365 days) (same day admission/separation cases were included in the '1 day' category)
- admission category (emergency or elective)
- diagnosis group (based on the first three digits of the principal diagnosis coded according to ICD-10-AM 4th Edition) The groups were specified using NHMD data for 2005–06.

*a) High-risk group, accounting for 80% of in-hospital mortality*

The first three characters of the principal diagnosis code (ICD-10-AM) were used to detect the conditions that (i) have the highest number of cases ending with the death of the patient in hospital and (ii) in aggregate, account for 80% of all deaths in hospital. In total, 68 three-character ICD-10-AM codes are in this set (see Table A1.1, Appendix 1).

*b) Lower risk group, accounting for the other 20% of in-hospital mortality*

This set includes cases with all principal diagnosis codes except the 68 in the 'high-risk' group. For the low risk of mortality analysis, rather than creating a separate coefficient for each of the 1,518 three-character principal diagnosis codes present in the group of cases that accounted for the remaining 20% of in-hospital mortality, a 10–category risk variable was created based on the crude risk of in-hospital mortality for each three-character diagnosis category. The risk categories are deciles of the log of the crude risk. Risk deciles were determined by calculating the absolute risk for each diagnosis group (i.e. taking all deaths in each diagnosis group and dividing by the total number of separations in the same diagnosis group). The log of the absolute risks was divided into 10 equal groups. Diagnoses that did not account for any deaths were included in the lowest decile of risk.

*c) 100% of in-hospital mortality*

The same risk approach as that defined in (b) was used. The data include 68+1,518=1,586 three-character ICD-10-AM diagnoses groups.

- comorbidity group (either 0, 1 or 2 and based on the Charlson Index score (Quan et al. 2005)). Comorbidity status was derived from the additional diagnosis codes in the NHMD, which were used to generate a Charlson Index score for each patient based on Quan's method (Quan et al. 2005). The Charlson Index was converted to a score of 0, 1 or 2. Patients whose Charlson Index value is 2 or higher were assigned a score of 2.
- inward transfer status (admission mode=1 indicating whether a patient was transferred from an acute institution)

### Women's and Children's hospitals (WCHs)

The effect of including WCHs in the analyses was assessed by comparing the HSMRs based on diagnoses for the leading 80% of in-hospital deaths with and without WCHs included in the logistic regression model.

# 4.6 Model checking

For each of the three analyses that used the RACM approach, models were assessed for goodness of fit, discriminatory power and explanatory power.

## 4.6.1 Goodness of fit

Goodness of fit was assessed using the Hosmer–Lemeshow (2000) goodness-of-fit statistic for 10 groups based on deciles of risk (StataCorp 2007).

## 4.6.2 Model discrimination

An assessment of the discriminatory power of each model was based on the c-statistic (area under the ROC).

## 4.6.3 Explanatory power

The pseudo-$R^2$ statistic is reported to assess the degree to which included variables decreased the unexplained variance in the data.

# 4.7 Calculation of 95% confidence intervals

### a) for HSMR point estimates

95% confidence intervals for the tables and caterpillar plots were calculated using Byar's approximation:

Lower confidence limit = $O/E*(1-1/(9*O) - 1.96 / (3*sqrt (O)))^3 * 100$

Upper confidence limit = $(O + 1)/E*(1- (1/(9*(O+1))) + 1.96 / (3*sqrt (O+1)))^3 * 100$

where O = observed number of deaths and E = Expected number of deaths.

**b) for funnel plots**

The confidence intervals displayed in funnel plots were calculated by assuming a Poisson (inverse gamma) distribution for the expected number of deaths. Intervals roughly equal to two and three standard deviations for the HSMR funnel plots were plotted.

# 4.8 Further development of the risk model

For the high-risk (80%) group, we compared HSMRs calculated using the RACM model with HSMRs calculated using our own ERM model (see Section 3.3.5). Although that model was based on the same variables as the RACM model, the effect of transforming independent variables such as age to more closely approximate the distributional characteristics of the logit curve was tested empirically. All significant two-way interactions in the regression model were tested separately in a main effects model using the LR test. All significant interactions were then included in a final model and removed one at a time: the effect of each removal being assessed using the LR test.

Once the final model was chosen, we split the data set into a development and validation data set (50% of the data for each) and assessed model fit on the validation set using the coefficients obtained from the developmental data set. This allows the assessment of whether or not the chosen model over-fitted the given data and would not perhaps fit so well on other data sets; for example, different years.

In addition, we also assessed the effect of the addition of the SEIFA index of disadvantage (as either a continuous or categorical variable) on the pseudo-$R^2$ statistic. (The SEIFA index is described in *Appendix 5 Data issues*.)

# 4.9 Longitudinal analysis

In Section 2.7.2 we described recent growth in longitudinal analysis of in-hospital mortality. This approach allows analysis of trends—a matter of considerable interest. It also provides a way to assess the extent to which information derived from a data source is informative about characteristics of hospitals, rather than reflecting random variation. The latter requires treatment of values of in-hospital mortality at several time-points as repeated measures.

A prominent recent example of this approach is the analysis of Dutch data reported by Heijink (2008). We opted to use the same approach, because this would allow comparison.

The method is described further in Section 5.10.1.

# 4.10 Statistical software

Data preparation and cleaning were carried out using SPSS Version 14.0 for Windows.

All other analysis, and preparation of caterpillar plots and funnel plots, was done using Stata Statistical Software, Release 10.