Work in progress on the Australian and New Zealand Intensive Care (ANZICS) Database

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Adelaide, South Australia

MRC Biostatistics Unit, Cambridge
12 November 2007
Dr John L. Moran
An outline of my talk today

1. The ANZICS adult patient database (APD)
2. ANZICS mortality and LOS outcomes 1993–2003
3. Quantitative indices reflecting provider ‘process-of-care’
4. Concluding comments
Overview

The ANZICS Adult Patient Database is the largest (bi-national) intensive care database in the world.

Currently contains > 700,000 intensive care submissions collected from 138 intensive care units (ICUs) in Australia and New Zealand since 1987.

Evolved from humble beginnings in recognition of the integral importance of high-quality databases to the practice, management, research and audit of clinical services.

Major advantage of a national database: ability to capture large amounts of data across a broad spectrum of diagnoses and interventions → especially important in critical care medicine.

Intensive care is expensive: consumes an estimated AUS$500m to AUS$1b per annum.

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Development and implementation of a high-quality clinical database: the Australian and New Zealand Intensive Care Society Adult Patient Database

Peter J. Stow\textsuperscript{a}, Graeme K. Hart\textsuperscript{b,c}, Tracey Higlett\textsuperscript{c,*}, Carol George\textsuperscript{a}, Robert Herkes\textsuperscript{d}, David McWilliam\textsuperscript{d}, Rinaldo Bellomo\textsuperscript{e}

for the ANZICS Database Management Committee

\textsuperscript{a}ANZICS Adult Patient Database (APD), Melbourne, Victoria 3053, Australia
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Stow et al:

- origins of ANZICS APD up to December 2003
  - 444,147 case records
  - collect raw physiology data
  - 121/167 Australian and 10/27 New Zealand ICUs
  - data submissions from contributing ICUs are voluntary.

Database evaluated according to criteria of the Directory of Clinical Audit Databases (DoCDAT) and the Arts et al framework.\(^2\)

Overall: ANZICS APD is a high-quality database representative of the Australian population; it does have some weaknesses:

- completeness of recruitment $< 80\%$
- some queries about reliability of coding (lack of intra-rater and inter-rater reliability testing).

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Hospital level and locality

In Australia and New Zealand, critical care services may be provided in

- **tertiary, metropolitan, rural or private hospitals**;
- **distances** between centres are often **large**, and there may be geographical or other barriers to the transfer of patients between different levels of care.
- Private and public funding models may result in differences in clinical practice.
- In Australia, 50% of hospital care is private.
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Mortality and association with mechanical ventilation

\[ n = 223,129, \text{ overall mortality 16.1\%, mean LOS 3.6 days. Hospital mortality decreased 4\% over 11 years.} \]
SMRs for individual ICUs

- Considerable uncertainty has been apportioned to estimates of mortality as reflected in the Standardised Mortality Ratio (SMR).\(^3\)

- Full ‘explanatory’ models are preferable to the limited purview of ‘algorithmic’ (APACHE, SAPS, MPM) models
  - Acute Physiology and Chronic Health Evaluation.

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Bootstrapped CIs of ranks (1993 – 1997)

95% CIs of ICU SMR ranks
Rank SMR order for FE and RE models 1993 – 2003

Site numbers by descending SMR rank according to fixed or random effects

SMR: 95% CI; green, fixed effects; orange, random effects

Site id: FE, blue; RE, black
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The outcomes paradigm

Is now a **dominant influence** within medicine, and *critical care* is no exception.\(^4\)

In the USA

- *Cleveland Health Quality Choice*
- initially greeted with some enthusiasm
- but upon its demise, described as either *martyr* or *failure*.

In the UK

- the performance of the paediatric cardiac surgical service at the *Royal Bristol infirmary*.

In Australia

- ANZICS data-base initiative
- the inquiry into the *Bundaberg Base Hospital, Queensland*.\(^5\)

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APACHE II\textsuperscript{6} and exploration of risk adjusted mortality in a cohort of 13 ICUs

- established the notion of ‘institutional’ or ‘provider’ comparisons within critical care, and
- introduced SMRs to the critical care literature.

From wherein has ensued a discordant debate regarding the relationship between the SMR and ICU performance or quality:

- SMR and its variability is problematic
- “mortality is unlikely to be a sufficient statistic for quality” (Spiegelhalter 1999)
- scoring systems at best describe ‘elements’ of performance.\textsuperscript{7}

\textsuperscript{6}Knaus, Draper \textit{et al} \textit{Ann Intern Med} 1986
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- looked at quality of care components
- at the sampled case-record level
- using both *structured explicit* and *implicit* review.

Although clinicians’ *subjective* assessment criteria

- identified differences between high and low mortality rate outliers
- *not* confirmed for any condition where *explicit structured process* criteria were used.

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Process II

Subsequent efforts to locate a relationship between mortality and ‘quality of care’ have been grounded in chart review and have been largely unsuccessful:

- in a surgical environment (Gibbs et al 2001)
- in a general medical setting (Best et al 1994, Thomas et al 1993, Park et al 1990)

‘Prevalent care processes’

- have not established a strong relationship.

Pitches et al on mortality and quality of care: Do hospitals with higher risk-adjusted mortality rates provide poorer quality care?[^9]

- the “notion that hospitals with higher risk-adjusted mortality rates have poorer quality care is neither consistent nor reliable”.

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- in a general medical setting (Best et al 1994, Thomas et al 1993, Park et al 1990)

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- have not established a strong relationship.

Pitches et al on mortality and quality of care: Do hospitals with higher risk-adjusted mortality rates provide poorer quality care? 9

- the “notion that hospitals with higher risk-adjusted mortality rates have poorer quality care is neither consistent nor reliable”.

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This argument has been advanced because of the large sample sizes required to demonstrate small to modest changes in (mortality) outcome.

However, the felicity with which process may be measured is no guarantee that “measuring … process and reporting performance will improve outcomes”.¹⁰

There is also a certain circularity in these arguments …

- reliance on outcome measures is criticised from the standpoint of process-of-care
- which finds its ultimate assessment in terms of its effect on precisely those outcomes which have been ‘rejected’ in the first place.

So what is to be done?

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Our strategy: patient efficiency

There would be advantage in establishing a quantitative index which would subsume the diversity of process-of-care.

Would enable provider ranking and formalised comparison with both indices of, and ranks based upon, mortality outcomes.

Idea: measure the patient’s ability to maximise ‘output’

- in particular, length of stay
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Conceptual foundation: from econometrics

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The objective of producers can be as simple as seeking to avoid waste

- by obtaining maximum outputs from given inputs
- or, by minimizing input use in the production of given outputs\(^\text{11}\).

The notion of productive efficiency corresponds to what we call technical efficiency.

M.J. Farrell (JRSS A 1957) was the first to measure productive efficiency empirically using linear programming techniques.

- He showed how to decompose cost efficiency into its technical and allocative components, and
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The influence of Farrell’s work

**Data envelope analysis (DEA)**

In an innovative study of patients with severe head trauma

- Nathanson *et al*\(^1\)\(^2\) used DEA to calculate individual patient ‘efficiency’ scores based upon the ability to *maximise cerebral perfusion pressure* (output)
  - for a given set of physiological inputs: temperature, MAP, serum osmolality, arterial \(PaCO_2\);
  - patients with high efficiency scores had improved functional outcomes on ICU discharge.

Of greater significance for us:

**Stochastic frontier analysis (SFA).**

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Production frontier models

A stochastic production frontier model:

\[ y_i = f(x_i; \beta) \exp(v_i) TE_i \quad i = 1, \ldots, I \]  

producers

\( y_i \) is the scalar output of producer \( i \), \( x_i \) is a vector of inputs used by producer \( i \), and \( \beta \) is a vector of ‘technology’ parameters to be estimated;

\[ TE_i = \frac{y_i}{f(x_i; \beta) \exp(v_i)} \]

- \( y_i \) achieves its maximum feasible value iff \( TE_i = 1 \)
- \( TE_i < 1 \) measures the shortfall of observed output from the maximum feasible output in an environment characterised by \( \exp(v_i) \), which can vary across producers.
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Technical efficiency for ANZICS patients

Stochastic production frontier model (log-linear $f$):\textsuperscript{13}

$$\log y_i = \beta_0 + \sum_{j=1}^{k} \beta_j \log x_{ij} + v_i - u_i$$

where $TE_i = \exp(-u_i)$

- $y_i$ is ICU/ hospital length of stay
- $x_{ij}$s are acute physiology score and chronic health evaluation variables
- $v_i \sim N(0, \sigma_v^2)$, $i = 1, \ldots, 215515$ (can vary across locality/level)
- $u_i > 0$, here assumed exponentially distributed
  - and allowed to be a function of appropriate individual explanatory variables.
  - Patient efficiency scaled $[0, 1]$.

\textsuperscript{13}Stata\textsuperscript{TM} module \texttt{frontier}
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\(^{13}\)Stata\textsuperscript{TM} module frontier
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\(^{13}\)Stata™ module frontier
Patient efficiency for tertiary hospitals by locality

Patients alive at discharge

[Graphs showing patient efficiency for different regions]
Patient efficiency for private hospitals by locality

Private NSW

Private SA

Private VIC

Private QLD

Private TAS

Kernel density estimate

Normal density
Patient efficiency for rural hospitals by locality

![Graphs showing patient efficiency for rural hospitals by locality.](image)
Patient efficiency by hospital locality/level/size
ANZICS 1993–2003 (N=35)

Pred.prob (green) T.effic (blue) S.mort ratio (magenta); 95%BCa CI
ANZICS 1993–2003: biplot of median TE and SMR

The ANZICS adult patient database (APD) ANZICS mortality and LOS outcomes 1993–2003 Quantitative indices reflecting provider ‘process of care’

Concluding comments
TE of SA tertiary hospitals: real correlates with hospital policy

ICU LOS efficiency (mean) estimates: geographical location & yearly admission number

<table>
<thead>
<tr>
<th>ICU geographical locality</th>
<th>Yearly admissions &lt; 711</th>
<th>Yearly admissions &gt; 711</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern Territory</td>
<td>0.616 0.719</td>
<td></td>
</tr>
<tr>
<td>New South Wales</td>
<td>0.625 0.683 0.729 0.754</td>
<td>0.723</td>
</tr>
<tr>
<td>Australian Capital Territory</td>
<td>0.692</td>
<td>0.748</td>
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<tr>
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<td></td>
<td>0.709 0.758</td>
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<tr>
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<td>0.644 0.644 0.647 0.721</td>
<td>0.685 0.741</td>
</tr>
<tr>
<td>Tasmania</td>
<td>0.579 0.632 0.649</td>
<td></td>
</tr>
</tbody>
</table>
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CLOS of ANZICS APD patients 1993-2003

- **Unit of analysis**
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- **Survivors**
  - we define LOS of non-survivors as >> maximum LOS of alive discharges
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ANZICS hazard of discharge by location

Hazard of alive hospital discharge: covariate adjusted

Time to discharge: days

Hazard of hospital discharge

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30

NT NSW ACT SA
VIC NZ QLD TAS

Hazard of discharge by location:
- NT
- NSW
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ANZICS hazard of discharge alive by hospital level

Hazard of alive rural hospital discharge

Hazard of alive metropolitan hospital discharge

Hazard of alive tertiary hospital discharge

Hazard of alive private hospital discharge

Quantitative indices reflecting provider ‘process of care’

Concluding comments
ANZICS hazard of death by hospital level

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Hazard of metropolitan hospital death

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Hazard of private hospital death
The ANZICS adult patient database (APD)
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Aim: find parametric distribution or similar to fit the smoothed hazard profiles

- the associated parameter estimates will serve as *indices of performance* of various descriptor units.

Use simple survival measures:

- time to peak hazard, \( TMAX \)
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ANZICS survivors: SSfol

Hospital-level:locality (20 levels)
ANZICS survivors: mortality, TE and CLOS by hospital locality/level/size
TE of deaths for metropolitan hospitals by locality

- Metropolitan NT
- Metropolitan NSW
- Metropolitan SA
- Metropolitan VIC
- Metropolitan NZ
- Metropolitan QLD
- Metropolitan TAS

Kernel density estimate vs Normal density
Survivors and non-survivors: mortality, TE and CLOS by hospital locality/level/size
Now adding KE by hospital locality/level/size
The future?

The ‘third revolution’ in medical care\textsuperscript{15} dates back to Florence Nightingale in the mid-19th century in the UK and Ernest Codman in the early 1900s in the US\textsuperscript{16}.

Disquiet has been generated by the past and current publishing of mortality outcome data.

The establishment of quantitative indices of patient \textit{process-of-care} may be a valuable complement to \textit{mortality outcome}, both at the administrative and clinical level.

Our focus

- critically-ill patients within the ICU
- recognise patient groups in cardiac surgery, acute myocardial infarction, stroke, pneumonia and acute renal failure, where similar outcome endeavours have been established.

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