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# Estimating the Number of Organ Donors in Australian Hospitals—Implications for Monitoring Organ Donation Practices

David Pilcher, MBBS, MRCP, FRACP, FCICM,<sup>1,2</sup> Laura Gladkis, BSc, PhD,<sup>3</sup> Byron Arcia, BBiotech, GDipEcon,<sup>3</sup> Michael Bailey, PhD,<sup>2</sup> David Cook, MB, BS, PhD, FANZCA, FCICM,<sup>3,4,5</sup> Yael Cass, BA, B SocStudies (Hons), LLB (Hons),<sup>3</sup> and Helen Opdam, MBBS, FRACP, FCICM<sup>3,6</sup>

**Background.** The Australian DonateLife Audit captures information on all deaths which occur in emergency departments, intensive care units and in those recently discharged from intensive care unit. This information provides the opportunity to estimate the number of donors expected, given present consent rates and contemporary donation practices. This may then allow benchmarking of performance between hospitals and jurisdictions. Our aim was to develop a method to estimate the number of donors using data from the DonateLife Audit on the basis of baseline patient characteristics alone. **Methods.** All intubated patient deaths at contributing hospitals were analyzed. Univariate comparisons of donors to nondonors were performed. A logistic regression model was developed to estimate expected donor numbers from data collected between July 2012 and December 2013. This was validated using data from January to April 2014. **Results.** Between July 2012 and April 2014, 6861 intubated patient deaths at 68 hospitals were listed on the DonateLife Audit of whom 553 (8.1%) were organ donors. Factors independently associated with organ donation included age, brain death, neurological diagnoses, chest x-ray findings, PaO<sub>2</sub>/FIO<sub>2</sub>, creatinine, alanine transaminase, cancer, cardiac arrest, chronic heart disease, and peripheral vascular disease. A highly discriminatory (area under the receiver operator characteristic, 0.940 [95% confidence interval, 0.924-0.957]) and well-calibrated prediction model was developed which accurately estimated donor numbers. Three hospitals appeared to have higher numbers of actual donors than expected. **Conclusions.** It is possible to estimate the expected number of organ donors. This may assist benchmarking of donation outcomes and interpretation of changes in donation rates over time.

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Transplantation has become the therapy of choice for many patients with end-stage organ failure. It is dependent on identification of potential organ donors by medical staff and support from family members. In 2009, the Australian Organ and Tissue Donation and Transplantation Authority was created to implement a set of national reforms to increase rates of organ and tissue donation.<sup>1</sup> This has been

associated with an annual increase in the number of deceased organ donors from 247 in 2009 to 391 in 2013 (11.3 to 16.9 donors per million population). These reforms included a requirement that the 74 hospitals with donation specialist staff undertake an audit of deaths, the DonateLife audit. The aims of the audit included raising awareness among hospital staff of missed donation opportunities, measuring the potential donor pool, and assessing performance in terms of rates of request, consent, and actual donation. A web-based data

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<sup>1</sup> Department of Intensive Care, The Alfred Hospital, Commercial Road, Prahran, VIC, Australia.

<sup>2</sup> Department of Epidemiology and Preventive Medicine, Australian and New Zealand Intensive Care - Research Centre, School of Public Health and Preventive Medicine, Monash University, VIC, Australia.

<sup>3</sup> DonateLife, The Australian Organ and Tissue Authority, ACT, Australia.

<sup>4</sup> Department of Intensive Care, Princess Alexandra Hospital, Brisbane, QLD, Australia.

<sup>5</sup> School of Mathematical Sciences, Queensland University of Technology, Brisbane, QLD, Australia.

<sup>6</sup> Department of Intensive Care Medicine, The Austin Hospital, Heidelberg, VIC, Australia.

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Correspondence: David Pilcher, MBBS, MRCP, FRACP, FCICM, Department of Intensive Care, The Alfred Hospital, Commercial Road, Prahran, Vic 3004, Australia. (d.pilcher@alfred.org.au).

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collection tool was introduced in July 2012 that enabled the collection of detailed physiological and laboratory data, in addition to information about patient demographics, brain death status, end-of-life process, and communication with the family about donation.

Measurement of donation rates and performance most commonly uses the metric of actual donors per million (living) population.<sup>2</sup> This is limited in that it does not account for the potential donor pool, which is dependent on rates and causes of death. Methodologies have been described that include accessing large administrative databases<sup>3-5</sup> to assess potential for organ and tissue donation. Their applicability to organ donation is unknown. More precise methods have used medical record review<sup>6-13</sup> but may in turn be limited by using objective but restrictive criteria, including presence of brain death and narrow age and medical suitability criteria. Estimation of potential donors after circulatory death may be particularly difficult where accurate prediction of time to death after withdrawal of cardiorespiratory support is required.<sup>14</sup> Application of specific criteria for graft selection may improve estimation of potential donor numbers.<sup>6,7,10,15</sup> However, the number of actual donors remains lower than the potential donor pool as a consequence of different identification, consent rates, and supportive therapies.

Donation cases are relatively rare events in most hospitals. Thus, to benchmark and appropriately compare the organ donation outcomes between hospitals, an accurate estimation of the expected number of donors is required. A true estimate should reflect contemporary medical practices,

identification, and consent rates, not just the theoretical potential donor pool.

Prediction modeling is common in many areas of health care. Mortality outcomes for patients undergoing cardiac surgery<sup>16</sup> after admission to intensive care unit (ICU)<sup>17-21</sup> are commonly compared using algorithms which can estimate predicted number of deaths. Techniques for creating these have been widely published but have not to our knowledge ever been applied to the organ donation sector.<sup>17</sup>

Our hypothesis was that data routinely collected through the DonateLife Audit could be used to estimate the true number of organ donors within contributing Australian hospitals. Our aim was to develop and test the applicability of such a prediction tool.

## MATERIALS AND METHODS

At participating hospitals, all patients aged between 28 days and 80 years who died in the ICU, emergency department or within 24 hours of discharge from the ICU or emergency department, were entered into the audit tool by dedicated organ donation specialist staff. The data tool used a hierarchical information capture structure where data collection ceases if certain criteria are met. For instance, any patient where organ donation was considered at any stage, full data collection is required even if the patient has medical contraindications to donation or is older than 80 years. However, if after entering basic demographic information, a patient has a history of active cancer and donation had

**TABLE 1.**

### Comparison of donors to patients who did not become donors

Total with available data	All patients (6861)	Not donors (6308)	Donors (553)	P	
Basic demographics					
Age, y	6861	61 [47-71]	62 [49-72]	48 [32-61]	<0.0001
Confirmed and probable brain dead	6861	14.8% (1016)	9.4% (594)	76.3% (422)	<0.0001
Length of stay in ICU, d	2444	4 [2-9]	4 [2-10]	3 [2-5]	<0.0001
Time (min) to death after withdrawal of cardiorespiratory support (non-brain dead patients only)	3216	17 [0-70]	17.5 [0-75]	17 [13-22]	0.86
Cardiac arrest during active treatment	6861	38.3% (2625)	42% (2623)	0.4% (2)	<0.0001
Organ donation assessed or considered by medical staff	6861	33.6% (2302)	28% (1751)	100% (553)	<0.0001
No request for donation because not medically suitable	6861	3.1% (213)	3.4% (213)	0% (0)	<0.0001
Discussion with family about donation <sup>a</sup>	6861	22.2% (1523)	16% (978)	98% (545)	<0.0001
Consent for donation <sup>b</sup>	1464	59.7% (874)	35.9% (330)	100% (544)	<0.0001
Cause of death					
Cerebral hypoxia	6861	13.7% (941)	12% (783)	29% (158)	<0.0001
Cerebral infarction	6861	2.3% (160)	2% (138)	4% (22)	
Intracranial haemorrhage	6861	13.4% (921)	11% (679)	44% (242)	
Traumatic brain injury	6861	5.5% (378)	4% (277)	18% (101)	
Non-neurological	6861	62.1% (4262)	67% (4248)	3% (14)	
Unknown	6861	0.6% (42)	0.7% (42)	0% (0)	
Organs donated					
Heart	6861	2% (140)	0% (0)	25% (140)	Not applicable
Kidney(s)	6861	7.3% (499)	0% (0)	90% (499)	
Liver	6861	4.8% (330)	0% (0)	60% (330)	
Lung(s)	6861	3.5% (241)	0% (0)	44% (241)	
Pancreas	6861	1.3% (90)	0% (0)	16% (90)	

All values reported as % (n) or median [interquartile range].

<sup>a</sup> For 8 donors information was unavailable about organ donation discussions.

<sup>b</sup> One donor was listed as having had no conversation with family (no further information was available).

not been considered, then only limited further information was required. To ensure data quality, validation rules were built into the data collection tool. Submitted data underwent further consistency and completeness checks centrally by the staff at DonateLife.

For this study, data submitted to the DonateLife Audit from contributing hospitals within 7 of the 8 states and territories of Australia were examined. Intubated patients, between the ages of 1 and 110 years inclusive, who had died within contributing hospitals between July 2012 and April 2014 were included. Patient identifiers were removed before submission of data from contributing hospitals. Names of hospitals and regions in Australia were removed from the data set subsequently used for analyses. For reporting of results by region, the 4 smaller states and territories of Australia were collapsed into one and were reported as a single region.

A donor was defined as a patient for whom the retrieval procedure (with surgical incision) commenced in the operating room for the purposes of retrieval of an organ for transplantation. This thus may have included patients in whom an organ was not removed because of the finding of

intraoperative unsuitability or where a retrieved organ may have been discarded before transplantation.

### Statistical Analysis

Univariable comparisons of donors and patients who were not donors were performed. Results were presented as proportions and medians with interquartile range. Wilcoxon rank sum test,  $\chi^2$  test, and *t* test were used to compare groups as appropriate, depending on the distribution of data.

A correlation matrix of variables was used to explore collinearity. Collinear variables were assessed using univariable logistic regression to choose the one with the greatest discrimination for inclusion in the final model. Continuous variables were initially converted to categorical variables with an additional category and coefficient generated for missing data before being dichotomized at clinically relevant cutoff points.

The prediction model was developed using logistic regression with both stepwise selection and backward elimination techniques with all variables with a univariable *P* value less than 0.10 considered for model inclusion, with the final model further assessed for clinical and biological plausibility.

**TABLE 2.**

#### Medical conditions and biochemical organ function values

Total with available data	All patients (6861)	Not donors (6308)	Donors (553)	<i>P</i>	
<b>Chronic medical conditions</b>					
Chronic heart disease	6861	17.1% (1174)	17.5% (1105)	12.6% (69)	0.002
Diabetes	6861	9.3% (639)	9.6% (604)	6.3% (35)	0.011
History of cancer	6861	14.8% (1016)	16% (1015)	0% (1)	<0.0001
Hypertension	6861	18.3% (1253)	18.1% (1142)	20.1% (111)	0.26
IV drug use	6861	2.6% (180)	2.7% (167)	2.4% (13)	0.67
Peripheral vascular disease	6861	4.6% (315)	4.9% (310)	0.9% (5)	<0.0001
<b>Hepatic</b>					
ALT, IU	2750	57 [26-158]	62 [27-184]	43 [24-87]	<0.0001
AST, IU	1810	77.5 [38-220]	88.5 [39-278]	53 [34-102]	<0.0001
Bilirubin, mmol	2748	12 [8-23]	13 [8-24]	12 [8-17]	0.0003
Chronic liver disease	6861	6.1% (418)	6.4% (402)	2.9% (16)	0.001
Previous hepatitis C	6861	3.2% (217)	3.3% (206)	2.0% (11)	0.1
<b>Respiratory</b>					
FiO <sub>2</sub> , %	2199	58.2 (28.8)	53.72 (26.55)	75.33 (30.43)	<0.0001
PaO <sub>2</sub> , mm Hg	2339	101 [79-158]	95 [76-128]	250 [109-402]	<0.0001
PaO <sub>2</sub> /FiO <sub>2</sub> ratio (highest in 24 hours prior to death)	2246	208 [110-312]	195 [102-290]	270 [151-368]	<0.0001
SaO <sub>2</sub> , %	2222	98 [95-99]	97 [94-99]	99 [98-100]	<0.0001
Chest X-ray clear or minor changes	2323	64.2% (1492)	59.8% (1106)	81% (387)	<0.0001
Chronic lung disease	6861	11.3% (775)	11.4% (718)	10.3% (57)	0.43
<b>Pancreatic</b>					
Amylase, IU	292	65.5 [36-142]	68 [27-155]	63 [37-134]	0.66
Lipase, IU	582	36.5 [16-94]	47 [22-138]	26 [14-63]	<0.0001
<b>Renal</b>					
Creatinine (lowest during admission)	3050	82 [60-120]	88 [63-128]	67 [54-86]	<0.0001
Creatinine (last before death)	3022	97 [65-166]	108 [69-178]	71 [56-97]	<0.0001
Creatinine (lowest in past 12 months before hospital admission)	1109	70 [55-91]	72 [55-93]	61 [50-75]	<0.0001
Creatinine on admission	2945	94 [69-136]	99 [72-145]	77 [63-102]	<0.0001
Renal replacement therapy in ICU	6861	9.0% (618)	9.6% (603)	2.7% (15)	<0.0001
Average hourly urine output, mL	2125	57 [25-100]	50 [20-95]	70 [50-100]	<0.0001
Chronic renal failure (on dialysis)	6861	3.2% (220)	3.4% (216)	0.7% (4)	0.0005

All values reported as % (n) or median [interquartile range].  
IV indicates intravenous.

The prediction model was derived using data from July 2012 to December 2013 with internal validation performed using a bootstrap technique using 200 repetitions and resampling of the whole derivation data set. A predicted likelihood of donation was calculated for all patients using the following formula:

Probability of being a donor =  $e^{\text{logit}} / (1 + e^{\text{logit}})$  where "logit =  $c + b_1x_1 + b_2x_2 + \dots + b_nx_n$ ",  $c$  is a constant,  $b_1$  to  $b_n$  are  $\beta$ -coefficients derived from the logistic regression model and  $x_1$  to  $x_n$  are the individual predictor variables.

External validation was performed by applying the same prediction model to data from 2014 and comparing observed and predicted outcomes. Discrimination and calibration were assessed using the area under the receiver operator characteristic and Hosmer-Lemeshow C statistic with associated  $P$  value. A ratio of actual to predicted donors was created for each submitting hospital and displayed on a funnel plot with Poisson distribution confidence intervals drawn around a ratio of unity. All analyses were performed using STATA version 12 (StataCorp, College Station, TX).

No information about ethnicity, management during the donation assessment, or consent discussions was included in the modeling. The project was approved as a low-risk research study (number 336/14) by the ethics committee of The Alfred Hospital.

## RESULTS

Ten thousand three hundred two patients from 68 hospitals were available for analysis, and of these 6861 had been

intubated and comprised the study data set. One thousand seven hundred fifty (26%) died between July and December 2012. Four thousand one hundred nineteen (60%) died during 2013, and 992 (14%) were listed as having died within the first 4 months of 2014. Five hundred fifty-three (8.1%) were organ donors.

Tables 1 and 2 show the characteristics of patients who became donors compared to those who did not. Donors were younger, spent less time in the ICU, were more likely to die with neurological conditions and be confirmed or probably brain dead, had lower prevalence of comorbid conditions, and better organ function tests.

Of the 3 creatinine values recorded (on admission to hospital, last before death, lowest in the past 12 months), a combined variable representing the lowest of the 2 values during the patient's hospitalization was most highly associated with successful organ donation. Of the 3 arterial blood gas values available, the highest  $\text{PaO}_2/\text{FiO}_2$  ratio was most predictive. Alanine transaminase (ALT) level was the most discriminatory of the liver function tests.

Table 3 shows the adjusted odds ratios for factors independently associated with likelihood of donation along with their relevant  $\beta$  coefficients. These included confirmed or likely brain death, specific neurological causes for death,  $\text{PaO}_2/\text{FiO}_2$  of 350 or greater, and a chest X-ray described as clear or with minimal changes. Factors which were associated with lower rates of donation included age older than 70 years, the presence of active cancer, cardiac arrest during active management, chronic heart disease, peripheral vascular disease, creatinine levels over 100  $\mu\text{mol}$ , and ALT of

**TABLE 3.**

**Logistic regression analysis of factors associated with organ donation (using 200 bootstrap repetitions with replacement of the complete data set—July 2012 to December 2013)**

	Adjusted odds ratio	95% CI	$\beta$ coefficient	$P$
Basic demographics				
Age $\geq$ 70 y	0.34	(0.23-0.51)	-1.068	<0.0001
Active cancer	0.03	(0.01-0.08)	-3.414	<0.0001
Cardiac arrest during active treatment	0.06	(0.02-0.18)	-2.881	<0.0001
Peripheral vascular disease	0.34	(0.11-1.01)	-1.094	0.048
Confirmed or probably brain dead	5.63	(4.26-7.43)	1.728	<0.0001
Cause of death				
Cerebral infarction	4.09	(1.87-8.94)	1.408	<0.0001
Cerebral hypoxia	6.84	(3.54-13.23)	1.923	<0.0001
Intracranial haemorrhage	8.00	(4.22-15.17)	2.080	<0.0001
Traumatic brain injury	8.34	(4.08-17.08)	2.122	<0.0001
Other neurological conditions	5.92	(2.54-13.83)	1.779	<0.0001
Cardiothoracic organ criteria				
$\text{PaO}_2/\text{FiO}_2$ ratio $\geq$ 350	1.33	(1.00-1.76)	0.285	0.036
Chest X ray "clear or minimal changes"	1.68	(1.29-2.20)	0.519	<0.0001
Chronic heart disease	0.55	(0.37-0.81)	-0.599	0.003
Abdominal organ criteria				
Creatinine $\geq$ 100 $\mu\text{mol}$	0.47	(0.34-0.65)	-0.752	<0.0001
ALT $\geq$ 200 IU	0.44	(0.31-0.64)	-0.811	<0.0001

Development data set (before 2014) = 5869 patients, pseudo  $R^2 = 0.483$ .

Area under receiver operator characteristic = 0.949 (95% CI, 0.943-0.956).

Hosmer-Lemeshow C statistic = 9.95,  $P = 0.19$ .

Validation data set (after 2014) = 992 patients.

Area under receiver operator characteristic = 0.940 (95% CI, 0.924-0.957).

Hosmer-Lemeshow C statistic = 4.94,  $P = 0.67$ .

Constant for logistic regression model = -3.796.

95% CI indicates 95% confidence interval.

**TABLE 4.****Actual and predicted numbers of donors across different regions of Australia**

	Brain dead donors		Non-brain dead donors	
	Actual	Predicted	Actual	Predicted
July 2012 to December 2013 (derivation)				
Region 1	110	96.2	24	27.3
Region 2	100	98.4	47	39.1
Region 3	67	74.9	24	23
Region 4	81	88.4	12	17.6
Total	358	357.9	107	107
January to April 2014 (validation)				
Region 1	23	19.1	6	5.6
Region 2	19	18.7	10	8.8
Region 3	13	12.2	4	4.3
Region 4	10	12.7	3	3
Total	65	62.7	23	21.7

200 IU or greater. Of note, hypertension, diabetes, chronic renal failure, and the need for dialysis during the hospital stay, although less common in donors, were not independently associated with a reduced odds of being an organ donor.

**Case Examples**

A 70-year-old who was not brain dead, had a history of hypertension and peripheral vascular disease, died from an intracerebral hemorrhage, had a creatinine of 99  $\mu\text{mol}$ , ALT of 29 IU, and clear chest X-ray had a 2.5% chance of being a donor.

A 33-year-old, who died from a traumatic brain injury, was brain dead, had no comorbidities, a clear chest X-ray, and normal biochemical values had a 70.2% chance of becoming a donor.

The prediction model was developed from the above factors to determine each person's estimated chance of becoming a donor. This showed excellent discrimination in both derivation and validation data sets with areas under the receiver operator characteristic of 0.949 (95% confidence interval, 0.943-0.956) and 0.940 (95% confidence interval, 0.924-0.957), respectively. The model also had good calibration in both derivation and validation data sets with Hosmer-Lemeshow C statistics of 9.95 ( $P = 0.19$ ) and 4.94 ( $P = 0.67$ ),

respectively, indicating that predicted numbers of donors were not different from observed.

Tables 4 and 5 show the predicted and actual numbers of donors within each region of Australia and across different hospital types. Figure 1 shows the ratio of observed to predicted donors at each of the hospitals over the whole period, charted on a funnel plot. Three hospitals were identified as having high donation ratios (i.e., more donors than expected). The combined consent rate at these 3 hospitals was higher than at the other hospitals overall (71% [115/163] vs 58% [759/1301],  $P = 0.003$ ). Figure 2 shows expected and actual donor numbers within each age group. Appendix 1 lists a calibration table comparing actual and predicted donors across 10 groups of risk.

**DISCUSSION**

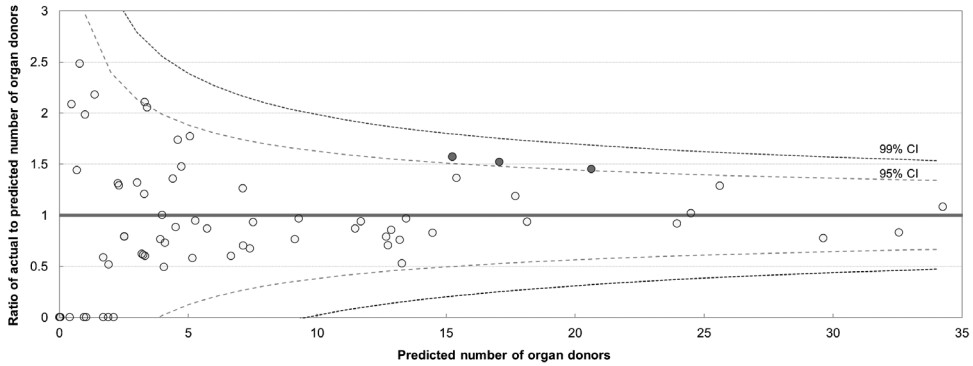
Using appropriate statistical techniques, it was possible to develop accurate estimates of the predicted number of donors within each hospital. Prospectively validating these estimations on data from 2014 confirmed their accuracy. By comparing actual and predicted donor numbers, it was possible to identify 3 hospitals which appeared to have higher donation rates than other Australian hospitals.

Previous publications have attempted to assess the maximum overall potential for donation.<sup>4,6-10,15</sup> Our approach has been to develop a technique to estimate expected donor numbers given present practices and consent rates. Although this is not a methodology for determining the overall maximum potential donor pool, it can provide a benchmark against which it is possible to compare actual donation outcomes. This may in turn facilitate identification of hospitals whose performance differs from their peer group, thereby allowing investigation of practices which can influence donation rates more widely (such as those that led to the higher consent rates at the 3 hospitals in this study).

Application of this technique may also help explain variations in donor numbers over time. For instance, if there were increased identification of donors, an improvement in consent rates (presently just under 60%) or wider introduction of processes, such as donation after circulatory death in more hospitals, one would expect an increase in the number of actual donors over predicted numbers. If there were a reduction in potential donors either through improved survival of neurosurgical patients or a relative increase in deaths among elderly patients with comorbidities who had medical contraindications to donation, this would be reflected in reduction in the predicted number of donors.

**TABLE 5.****Actual and predicted numbers of donors in different hospital types**

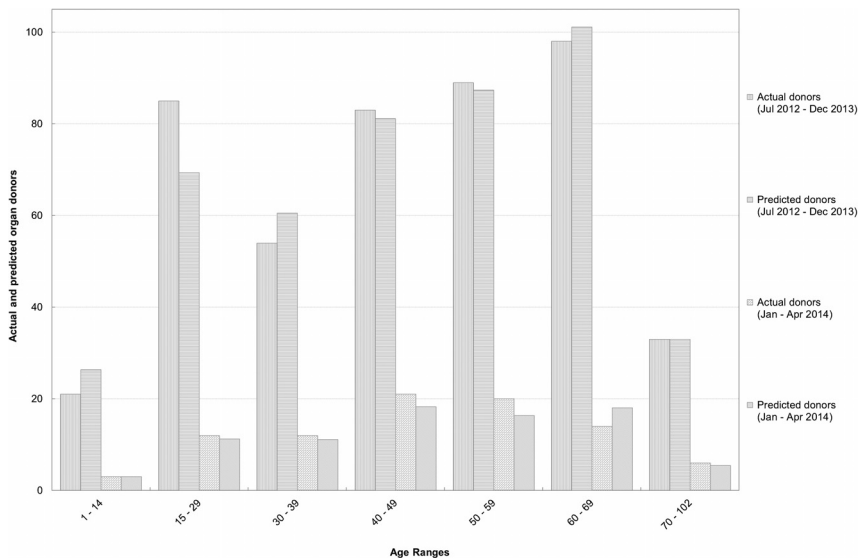
	No. hospitals	July 2012 to December 2013 (derivation)		January to April 2014 (validation)	
		Actual	Predicted	Actual	Predicted
Metropolitan	13	56	60.5	15	16.8
Private	4	1	0.8	0	0
Rural/regional	23	42	46.7	10	7.5
Tertiary	28	366	357	63	60.1
Total	68	465	465	88	84.4



**FIGURE 1.** Funnel plot of ratio of actual to predicted number of organ donors. Data shown represent information from all hospitals for the time period July 2012 and April 2014. The 95% and 99% (Poisson distribution) confidence limits are shown as light dotted grey and dark grey lines, respectively.

The strengths of this technique are that it has been developed on a relatively large data set of deaths using data that is collected by dedicated, funded, and trained donation nursing staff who regularly feedback the results of the audit regularly to clinicians. In addition, built-in validation rules and dedicated audit staff locally and centrally at DonateLife ensure that obvious data errors are promptly corrected. Thus, although the specific accuracy of data is unknown, it is likely to be of a high quality. The prediction tool also demonstrated excellent discrimination and calibration in both brain dead and non-brain dead patients. The latter group comprises the potential donors after cardiac death where there has been little published work on estimation of true donation potential.<sup>22,23</sup> Pediatric donors are rare,<sup>24</sup> and the estimated number of possible donors is unknown. The prediction tool was equally applicable to adults and children. Although guidelines for identification of potential donors and for obtaining consent exist in some countries,<sup>25</sup> application of this technique to identify hospitals who have successfully implemented techniques leading to increased numbers of donors (as seen at the three hospitals in this study) may provide valuable practical information to the whole health care sector.

However, there are limitations. This technique has not previously been used to estimate donor numbers. A relatively small cohort from 2014 has been used for validation. It was not possible to determine any effect on likelihood of donation because of the variation in acceptance criteria by transplant hospitals. The performance of these techniques in estimating donor numbers may need further testing in future. There may be a degree of “self-fulfilling” prophecy due to the hierarchical nature of the data collection. Actual and potential donors are more likely to get information recorded and thus artificially elevate the ability of individual variables to accurately contribute to donor number estimation. Although a strength of the modeling is that predictive variables are potentially available before donation, this technique cannot prospectively estimate donor numbers because it presently relies on an analysis of deaths which have already occurred within a hospital. This methodology ascribes each individual “predicted chance of being a donor” which may limit its clinical “bedside” applicability at an individual patient level. However, the ability to identify individuals with a low chance of donation, who do go on to become donors and vice versa, may allow clinicians to identify generic enablers and barriers



**FIGURE 2.** Actual and predicted donors within each age group. Vertical striped bars represent actual donors from July 2012 to December 2013. Horizontal striped bars represent predicted donors from July 2012 to December 2013. Brick pattern bars represent actual donor from January 2013 to April 2014. Diagonal pattern bars represent predicted donor from January 2013 to April 2014.

to donation. Although methods for benchmarking organ donation practice between hospitals have been published previously,<sup>26</sup> the most appropriate application for techniques described here (e.g., at individual, institutional, or regional levels) is unknown. In addition, although this study did not identify any hospitals which had less donors than predicted, there is the capacity to do so. Should this occur, mechanisms for appropriate analysis and feedback without presumption of “poor performance” must be in place. Finally, this technique has been developed only within hospitals, which contribute to the DonateLife Audit, and applicability to other hospitals in Australia and abroad is unknown.

In conclusion, it was possible to develop a prediction algorithm on the basis of baseline patient characteristics which allowed accurate estimation of donor numbers at hospitals contributing to the DonateLife Audit. Application of these techniques may assist in interpretation and estimation of donation trends in Australia.

## REFERENCES

1. Australian Organ and Tissue Donation and Transplantation Authority Act 2008, vol No. 122 2008.
2. Australian and New Zealand Organ Donation Registry.
3. Canadian Blood Services. Estimating Potential Tissue Donors in Canada from 2005-2008: An Update Based on Acute Care Hospital Admissions Data January 2014, 2014.
4. Galea G. Estimating the potential of tissue donation in Scotland. *Scott Med J*. 2012;57(4):185.
5. Procaccio F, Ricci A, Ghirardini A, et al. Deaths with acute cerebral lesions in ICU: Does the number of potential organ donors depend on predictable factors? *Minerva Anesthesiol*. 2014.
6. Opdam HI, Silvester W. Potential for organ donation in Victoria: an audit of hospital deaths. *Med J Aust*. 2006;185(5):250–254.
7. Sheehy E, Conrad SL, Brigham LE, et al. Estimating the number of potential organ donors in the United States. *N Engl J Med*. 2003;349(7):667–674.
8. Wesslau C, Grosse K, Krüger R, et al. How large is the organ donor potential in Germany? Results of an analysis of data collected on deceased with primary and secondary brain damage in intensive care unit from 2002 to 2005. *Transpl Int*. 2007;20(2):147–155.
9. Opdam HI, Silvester W. Identifying the potential organ donor: an audit of hospital deaths. *Intensive Care Med*. 2004;30(7):1390–1397.
10. Madsen M, Bøgh L. Estimating the organ donor potential in Denmark: a prospective analysis of deaths in intensive care units in northern Denmark. *Transplant Proc*. 2005;37(8):3258–3259.
11. Guadagnoli E, Christiansen CL, Beasley CL. Potential organ-donor supply and efficiency of organ procurement organizations. *Health Care Financ Rev*. 2003;24(4):101–110.
12. Christiansen CL, Gortmaker SL, Williams JM, et al. A method for estimating solid organ donor potential by organ procurement region. *Am J Public Health*. 1998;88(11):1645–1650.
13. de la Rosa G, Domínguez-Gil B, Matesanz R, et al. Continuously evaluating performance in deceased donation: the Spanish quality assurance program. *Am J Transplant*. 2012;12(9):2507–2513.
14. Brieva J, Coleman N, Lacey J, et al. Prediction of death in less than 60 minutes after withdrawal of cardiorespiratory support in potential organ donors after circulatory death. *Transplantation*. 2014;98(10):1112–1118.
15. Lesieur O, Leloup M, Gonzalez F, et al. Eligibility for organ donation following end-of-life decisions: a study performed in 43 French intensive care units. *Intensive Care Med*. 2014;40(9):1323–1331.
16. Billah B, Huq MM, Smith JA, et al. AusSCORE II in predicting 30-day mortality after isolated coronary artery bypass grafting in Australia and New Zealand. *J Thorac Cardiovasc Surg*. 2014;148(5):1850–1855.
17. Paul E, Bailey M, Pilcher D. Risk prediction of hospital mortality for adult patients admitted to Australian and New Zealand intensive care units: development and validation of the Australian and New Zealand Risk of Death model. *J Crit Care*. 2013;28(6):935–941.
18. Knaus WA, Draper EA, Wagner DP, et al. APACHE II: a severity of disease classification system. *Crit Care Med*. 1985;13(10):818–829.
19. Knaus WA, Wagner DP, Draper EA, et al. The APACHE III prognostic system. Risk prediction of hospital mortality for critically ill hospitalized adults. *Chest*. 1991;100(6):1619–1636.
20. Harrison DA, Patel K, Nixon E, et al. Development and validation of risk models to predict outcomes following in-hospital cardiac arrest attended by a hospital-based resuscitation team. *Resuscitation*. 2014;85(8):993–1000.
21. Harrison DA, Parry GJ, Carpenter JR, et al. A new risk prediction model for critical care: the Intensive Care National Audit & Research Centre (ICNARC) model. *Crit Care Med*. 2007;35(4):1091.
22. Opdam H. The rise and rise of donation after cardiac death: a solution to the shortfall in organs for transplantation? *Crit Care Resusc*. 2013;15(1):3–4.
23. Manara AR, Murphy PG, O'Callaghan G. Donation after circulatory death. *Br J Anaesth*. 2012;108(Suppl 1):i108–i121.
24. Workman JK, Myrick CW, Meyers RL, et al. Pediatric organ donation and transplantation. *Pediatrics*. 2013;131(6):e1723–e1730.
25. Chamberlain K, Baker MR, Kandaswamy P, et al. Donor identification and consent for deceased organ donation: summary of NICE guidance. *BMJ*. 2012;344:e341.
26. Matesanz R, Coll E, Domínguez-Gil B, et al. Benchmarking in the process of donation after brain death: a methodology to identify best performer hospitals. *Am J Transplant*. 2012;12(9):2498–2506.

## APPENDIX 1.

### Calibration table of all patients comparing actual to predicted donors across ranges of risk

Predicted chance of donation (%)	Actual donors	Predicted donors
0-9	0.7% (39/5481)	0.8% (46/5481)
10-19	18.0% (64/356)	14.2% (51/356)
20-29	28.1% (93/331)	24.4% (81/331)
30-39	36.6% (41/112)	35.3% (40/112)
40-49	47.1% (72/153)	45.1% (69/153)
50-59	44.2% (76/172)	55.1% (95/172)
60-69	67.2% (154/229)	65.4% (150/229)
70-79	51.9% (14/27)	70.2% (19/27)
80-100	0.0% (0/0)	0.0% (0/0)
Total	100.0% (553/6861)	100.0% (549/6861)