**A lifetime stroke outcome model: A patient level simulation tool for predicting lifetime secondary care use by patients who have been discharged from hospital following a stroke**

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**Abstract**

Introduction

Economic models of intervention in acute stoke care often rely on models to extrapolate short term outcomes into longer term outcomes required by decision makers. However, there is little consistency between the methods of extrapolation used. This presents challenges when interpreting estimated of long-term cost effectiveness

Patients and methods

A retrospective cohort of 1,500 patients discharges after stroke between 2013 and 2014 were followed for up to ten years and parametric equations representing their life-time risk of mortality and secondary resource use were estimated based on their levels of dependency, ages and sexes were developed.

Results

Two equations for mortality were developed. The first logistic model estimating mortality within twelve months of discharge, and a second Gompertz model estimating mortality over the remainder of the life course. A&E admissions were modelled using a Weibull distribution while non-elective bed days and elective bed days were both modelled using a loglogistic distribution. All equations include age, sex and modified Rankin score at discharge.

Discussion

Using data about patients outside of clinical trials, the risk equations allow extrapolation of results from short term trials over the life course in a range of lifetime models. Resources modelled are restricted to secondary care within a single trust but can be extended through future linkage with other data sets.

Conclusion

Our model is the first published set of risk equations for use in economic models of acute stroke interventions. Their use provides the opportunity to improve the consistency of modelling the longer-term effects of acute interventions.

**Background and Aim and Objectives**

The effects of a stroke on individuals can persist across the life course. Studies into the effectiveness and cost-effectiveness of interventions aimed at improving outcomes in the acute period often follow individuals for a relatively short time frame. Longer term consequences are typically estimated by extrapolating from short term consequences over the life course. Lifetime estimates of relative cost effectiveness, which are often required by decision makers, are therefore dependent on the assumptions made when extrapolating short term outcomes. Informing extrapolation by modelling life-expectancy, and consequent healthcare usage, using computer simulations method of estimating the lifetime effects of developments in the treatment of acute stroke. These models address the practical limitations of limited follow-up of patients in clinical studies. They typically do this by applying assumed relationships between population mortality and the additional mortality observed in the post-stroke population and with assumptions about the risk of recurrent stroke and its assumed effect on mortality. Whilst models based on these types of assumptions typically account for uncertainty by varying probabilities, they lack the fidelity to make individual predictions based on patient level data. Furthermore, there are no standard models available to extrapolate effect. This means that it can be difficult to compare post-follow up estimates of effect. Indeed, the European Stroke Organisation’s Health Economics Working Group recommended the ‘Development of resources for the standardisation of economic evaluation’ [[1]](#endnote-1). In other disease areas, notably Diabetes, models including the United Kingdom Prospective Diabetes Study Outcomes Model i[[2]](#endnote-2) that can be used to make predictions about individual patients have been developed to estimate the lifetime effects of interventions that are designed to affect the life-time probability of complications of diabetes. Diabetes models typically have large numbers of inputs to reflect the known risk factors associated with complications. In contrast, a lifetime stroke model developed to extrapolate the results of clinical trials would have fewer inputs. These should be restricted to those available at time of discharge. The aim of this study is to develop a set of equations that can be used in simulation studies that can be used to model lifetime effects of secondary care utilisation based on circumstances at discharge. The objectives are to use a retrospective cohort of stroke patients to develop the equations, to do so in such a way that that they can easily be incorporated into a range models developed in a range of computing environments and to illustrate how they may be incorporated into models of cost-effectiveness. This is to promote the use of a common set of predictors of events over the life course and increasing the comparability of models used to extrapolate the effects of differing treatments.

**Methods**

The major objective of this model is to simulate lifetime secondary care use by stroke patients after discharge from hospital as well as to calculate life expectancy. It is a patient level epidemiological model for a population of adults. The model integrates a set of risk equations for secondary care usage after discharge with a mortality equation. The inputs to the model are restricted to age at discharge, sex, and modified Rankin Score at discharge. The model is designed to be used in either discrete time or discrete event simulations. The risk equations for secondary care usage are for non-elective admissions, elective admissions, and A&E attendances. By combining predictions of resource use with predictions of mortality, annual estimates resource utilisation based on model inputs can be modelled.

*Risk Equations*

We derive five equations that can be used to estimate life expectancy and lifetime secondary care usage. Each equation takes modified Rankin Score at discharge, age at stroke onset and sex as inputs and predicts survival or resource use. Risk equations based on parametric relationships that reflect the nature of the underlying data. Risk equations for mortality were developed to take account of status in different years. There are two equations for mortality. The first, a logistic prediction of death in the 12 months following discharge. The second, a Gompertz model for times post the 12 months since discharge, in which the hazard of death increases exponentially with time. Increased mortality risk in the 12months following discharge followed by lower risks in subsequent years means they are unsuitable for use during this period as the hazard of death potentially decreases. Gompertz models have several advantages which make them suitable for modelling. For example, the probability of death at any one time can be calculated as can the time of death based on a probability. This follows the approach taken in the UKPDS Outcome model. The remaining three equations predict resource usage for secondary care events consisting of A&E admissions, non-elective bed days, and elective bed days. Survival functions were chosen to represent increasing resource use over time[[3]](#endnote-3). The algorithms provided in the Supplementary Materials are suitable for use in both discrete-event and discrete time models.

*Study subjects and outcomes*

1,509 stroke patient who were discharged from an acute stroke hospital in the northeast of England between 1 January 2013 and 31 December 2014 were followed up from discharge from index stroke event until 2 April 2021, with information about subsequent deaths, A&E attendances (annual count), elective (annual total length of stays) and non-elective admissions (annual total length of stays)

*Statistical Analyses*

The availability of population mortality, in the form of life tables, means that it is possible to extrapolate beyond the observed data. Extrapolation of secondary care data is possible because of the forms of the cumulative functions. Age at stroke onset was centred on the mean age of the cohort in the case of the Gompertz survival models and resource utilisation models. In the case of one year survival age was centred on the mean of the mRS.

*Extrapolating survival*

The requirement to be able to extrapolate effects over the life course required running a simulation based on survival in the observed data and life tables. The first stage of this required the creation of a cohort of patients who had not had strokes based on the age and sex distribution of our 1,509 patients. Then using data from life table, each patient in that cohort was allocated a random day of death based on life tables and a Gompertz model estimated. This allocation of a random day of death based on age and sex and estimation of a Gompertz model was repeated 10,000 times and a set of hazard ratios for death was estimated for each state captured by the modified Rankin compared to the cohort of non-stroke patients. These hazard ratios, along with the gamma parameter (rate of increase in mortality over time) of the Gompertz model were then used in a second simulation. During the second simulation, each stroke patient surviving at censor was given a random date of death, based on their age, sex and hazard ratio associated with their modified Rankin Score at discharge (estimated during first simulation). Lifespan was truncated at 100 years of age and the simulation was run 10,000 times to estimate the lifetime Gompertz model. The additional risk of death associated with each modified Rankin state compared to the UK population was applied to the risk of death (from life tables) for those alive at censor.

*Estimating Secondary Care Resource Utilisation*

The appropriate distribution of each of the resource use was chosen based on the Akaike information criterion (AIC). Choice of model was also influenced by their suitability for extrapolation. As such, A&E admissions were modelled using a Weibull distribution while non-elective bed days and elective bed days were both modelled using a loglogistic distribution. For each A&E attendance the cumulative count was increased on the day of the attendance unless it occurred at the same time as a non-elective admission. Elective and non-elective admissions were accounted for in terms of cumulative days of bed occupancy. For example, a non-elective admission lasting fifteen days was modelled as fifteen sequential bed days.

All analyses were carried out in Stata and R. Statas’ streg command was used to estimate survival to allow for multiple events per patient in the case of secondary resource use.

**Results**

*Baseline Characteristics*

There were 1,509 patients in the cohort, and it contained information about 7,110.53 post discharge patient years and just over half the patients were male and their mean age was 74. At censor date 44.40% of patients were alive, ranging from no patients discharged with an mRs of 5 to 71.94% with an mRs of zero. Further details of the cohort are shown in Table 1.

Table 1 Baseline characteristics at discharge by modified Rankin scale at discharge.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Total (n=1,509)** | **mRS 0 (n=139)** | **mRS 1 (n=333)** | **mRS 2 (n=366)** | **mRS 3 (n=359)** | **mRS 4 (n=268)** | **mRS 5 (n=44)** |
| Follow-up (Years) | 7110.53 | 881.16 | 1988.46 | 1965.13 | 1457.13 | 774.16 | 44.49 |
| Mean Age (Years) | 73.69 | 67.15 | 68.53 | 72.57 | 77.17 | 79.03 | 81.84 |
| Male (%) | 50.96 | 69.06 | 60.36 | 52.73 | 45.68 | 37.69 | 31.82 |
| Alive at censor (%) | 44.40 | 71.94 | 65.47 | 51.64 | 30.92 | 19.40 | 0 |
| Median NIHSS (IQR) | 3 (2 to 8) | 2 (1 to 3) | 2 (1 to 4) | 3 (2 to 5) | 5 (3 to 10) | 10 (4 to 18) | 17 (8 to 22) |
| Ischaemic (%) | 90.08 | 95.61 | 95.00 | 93.71 | 85.27 | 80.43 | 86.23 |
| Diabetes (%) | 15.77 | 12.95 | 14.11 | 19.67 | 15.60 | 14.55 | 13.64 |
| Atrial fibrillation (%) | 14.38 | 7.19 | 12.31 | 12.57 | 16.99 | 18.66 | 20.45 |
| Hypertension (%) | 47.18 | 41.01 | 48.65 | 45.63 | 49.03 | 48.88 | 43.18 |
| Mean Pre stroke mRS | 0.94 | 0.13 | 0.41 | 0.74 | 1.34 | 1.88 | 2.61 |
| Thrombolysed (%) | 12.76 | 11.51 | 9.31 | 12.02 | 14.21 | 11.57 | 20.45 |
| A&E Attendances (mean) | 4.09 | 4.78 | 4.04 | 4.49 | 4.57 | 3.08 | 1.18 |
| Non-Elective Bed Days (mean) | 23.24 | 15.41 | 17.19 | 26.13 | 32.90 | 20.80 | 5.68 |
| Elective Bed-days (mean) | 1.20 | 1.23 | 1.43 | 1.57 | 0.99 | 0.74 | 0.73 |

Ischaemic strokes made up 90% of our cohort, with prevalence’s of 16%,15% and 47% for diabetes, atrial fibrillation, and hypertension. Percentage of men decreased with mRS whilst age and stroke severity (NIHSS) increased. We observed 252 deaths within 12 months and 587 between month 13 and censor. There was a total of 6137 A& Attendances, 4,234 non elective admissions (accounting for 35,063 bed days) and 1,255 non-elective admissions (accounting for 1,770 bed days). Five diagnoses accounted for 18% of non-elective admissions (Pneumonia (except that caused by TB), Other connective tissue disease, Acute cerebrovascular disease, Urinary tract infections and Nonspecific chest pain). Further details of primary diagnoses of non-elective admissions are shown in supplementary material.

*Statistical Models*

The results of the two analyses to predict mortality in the twelve months following discharge are shown in Table 2. The risk of mortality with 12 months decreased with age and was greater for men. Higher mRS was associated with a higher risk of death, except for those with an mRS of 1 who had a small and statistically insignificant greater risk than those with mRS 0.

Table 2 Survival Analyses

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Year One Logistic | | | | Gompertz Hazard | | | | |
| Variable | Coef | SE | 95% CI | Coef | | SD | 95% CI |
| Constant | -4.2354 | 0.6057 | -5.4226, -3.0483 | -9.067 | | 0.1416 | -9.3093 -9.2968 |
| Gamma | - | - | - | 0.0002 | | 0.00001 | 0.0002, 0.0002 |
| Age at onset ¹ | 0.0663 | 0.0082 | 0.0503, 0.0823 | 0.0073 | | 0.0164 | -0.0203, 0.0334 |
| Age at onset squared ¹ | - | - | - | 0.0006 | | 0.0001 | 0.0004, 0.0008 |
| Male | 0.2636 | 0.1601 | -0.0389, 0.5904 | 0.1782 | | 0.0436 | 0.1048, 0.2490 |
| mrs 1 \* Age at onset ¹ | - | - | - | -0.0204 | | 0.007 | -0.0319, -0.0089 |
| mrs 2 \* Age at onset ¹ | - | - | - | -0.0259 | | 0.0069 | -0.0372, -0.0145 |
| mrs 3 \* Age at onset ¹ | - | - | - | -0.0256 | | 0.007 | -0.0372, -0.0142 |
| mrs 4 \* Age at onset ¹ | - | - | - | -0.0313 | | 0.0078 | -0.0444, -0.0185 |
| mrs 5 \* Age at onset ¹ | - | - | - | -0.1386 | | 0.0066 | -0.1494, -0.1277 |
| mrs 1 | 0.9539 | 0.6403 | -0.3012, 2.2089 | 0.2301 | | 0.0835 | 0.0920, 0.3646 |
| mrs 2 | 1.2590 | 0.6240 | 0.0360, 2.4821 | 0.4114 | | 0.1249 | 0.2058, 0.6162 |
| mrs 3 | 2.4773 | 0.6058 | 1.2900, 3.6646 | 0.6847 | | 0.1774 | 0.3848, 0.9774 |
| mrs 4 | 3.7310 | 0.6079 | 1.2901 3.6646 | 0.8535 | | 0.2136 | 0.5020, 1,2061 |
| mrs 5 | 4.9444 | 0.6795 | 3.6126, 6.2763 | 1.7763 | | 0.2364 | 1.3851, 2.1603 |
| ¹ Age variables are mean centred. The Gompertz model mean is 73.7324 years. The logistic model uses centred group means on mRS. These are 67.09161, 67.98058, 72.85753, 76.48837, 78.56029, 80.91837 for mRS 0-5 respectively | | | | | | | | |

After 12 months, men had a greater risk of death, risk of death increased with age at stroke and at an increasing rate. Higher mRS at discharge was associated with a higher risk of death, but in all cases, this increased risk was reduced as age at discharge increased.

The models for secondary care use over the period of analysis show that A&E visits are higher for men than women and decrease with age. Compared to an individual with a mRS of 0, the same individual would have a higher count of A&E visits if their mRS was 1 but a lower count if their mRS was 2 or higher. For the non-elective bed days, total bed day count decreased as age increased, with females having a higher number of bed days compared to men (all other variables being the same). The total number of non-elective bed days increased as the mRS increased, except for mRS of 5. An individual with a mRS of 5 could expect a higher total number of non-elective bed days than the same individual with an mRS of 1 but a lower total bed days than if they had a mRS of 2. For the elective bed days, the total count increased with age and if the individual was a man. Compared to an individual with a mRS of 0, the same individual would have a higher elective bed day count if their mRS was 1,2 or 5 but a lower total count if their mRS was 3 or 4.

Table 3 Resource use survival models

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **A&E (Weibull)** | | | **NEL Days (log-logistic)** | | | **EL Days (log-logistic)** | | |
|  | Coeff | SE | 95%CI | Coeff | SE | 95%CI | Coeff | SE | 95%CI |
| Constant | -0.0692 | 0.0601 | -0.187, 0.0487 | -1.3340 | 0.0329 | -1.3985,  -1.2695 | 1.2735 | 0.1167 | 1.0448, 1.5023 |
| Age 1 | -0.0050 | 0.0014 | -0.0076,  -0.0023 | -0.0248 | 0.0008 | -0.0264,  -0.0233 | -0.0081 | 0.0032 | -0.0144,  -0.0019 |
| Male | 0.0791 | 0.0331 | 0.0141, 0.1442 | 0.2966 | 0.0198 | 0.2577,  0.3354 | -0.0774 | 0.0720 | -0.2184, 0.0637 |
| mRS 1 | 0.1534 | 0.0614 | 0.0330, 0.2738 | -0.0468 | 0.0383 | -0.1218,  0.0283 | -0.7988 | 0.1273 | -1.0484,  -0.5492 |
| mRS 2 | -0.1126 | 0.0595 | -0.2291, 0.004 | -0.4899 | 0.0356 | -0.5598,  -0.4201 | -0.8763 | 0.1288 | -1.1287,  -0.6239 |
| mRS 3 | -0.4520 | 0.0597 | -0.5691,  -0.3349 | -1.1523 | 0.0358 | -1.2225,  -1.0821 | -0.1613 | 0.1331 | -0.4221, 0.0995 |
| mRS 4 | -0.3794 | 0.0674 | -0.5115,  -0.2474 | -1.2986 | 0.0386 | -1.3743,  -1.2229 | 0.1961 | 0.1586 | -0.1147, 0.5069 |
| mRS 5 | -0.3181 | 0.1808 | -0.6724, 0.0362 | -0.6244 | 0.0738 | -0.7689,  -0.4798 | -1.7254 | 0.2908 | -2.2953,  -1.1555 |
| ancillary parameter | 0.8167 |  |  | 0.1617 |  |  | 0.8516 |  |  |
| ¹ Age variables are mean centred. The hazard functions model mean is 73.7324 years. | | | | | | | | | | |

*Predictions*

Detailed instructions for using the predictive equations are given in the Supplementary Material. Using the two sets of equations (Table 2 and Table 3) we can make predictions about the likely life expectancy of people discharged from hospital following a stroke based on their age at time of stroke, their sex and their mRS at time of discharge. Table 4 shows the estimated median life expectancy (time when probability of being alive is 0.5). By combining this with expected annual resource use, we can derive estimates for the secondary resources consumed over the lifetime of the patient. For example, a 75-year-old male discharged from hospital with an mRS of 3 would be expected to live (on average) 3.35 years and would have 1.88 A&E Attendances, 20.79 non-elective bed days and 0.79 elective bed days over their lifetime.

Table 4 Sample predictions

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Patient at discharge** | **Survival Median (IQR)** | **Lifetime Secondary Resource Use** | | | **Average Annual Secondary Resource Use** | | |
| **A&E attendances** | **Non-Elective bed days** | **Elective bed-days** | **A&E attendances** | **Non-Elective bed days** | **Elective bed-days** |
| Male, 75, mRs 3 | 3.35 (1.61 to 4.87) | 1.88 | 20.79 | 0.79 | 0.56 | 6.18 | 0.24 |
| Female 55 mRs 2 | 13.75 (8.74 to 17.32) | 7.88 | 24.75 | 2.52 | 0.58 | 1.8 | 0.18 |
| Female 80 mRs 3 | 2.92 (1.45 to 4.23) | 1.54 | 22.54 | 0.69 | 0.53 | 7.71 | 0.24 |
| Male 66 mRs 4 | 3.32 (0.96 to 5.35) | 2.08 | 19.95 | 0.59 | 0.63 | 5.99 | 0.18 |
| Female 78 mRs 1 | 5.56 (3.12 to 7.60) | 4.17 | 20.69 | 1.74 | 0.75 | 3.71 | 0.31 |
| Male 80 mRs 5 | 0.55 (0.23 to 1.11) | 0.48 | 6.45 | 0.65 | 0.87 | 11.73 | 1.18 |
| Male 73 mRs 2 | 5.69 (3.22 to 7.75) | 3.8 | 20.22 | 1.84 | 0.67 | 3.55 | 0.32 |
| Female 76 mRs 4 | 2.00 (0.69 to 3.43) | 1.24 | 20.19 | 0.34 | 0.62 | 10.05 | 0.17 |
| Male 66 mRs 5 | 1.01 (0.42 to 3.05) | 0.83 | 8.05 | 0.97 | 0.82 | 7.97 | 0.96 |
| Female 68 mRs 0 | 12.62 (7.94 to 16.02) | 7.47 | 24.07 | 1.69 | 0.59 | 1.9 | 0.13 |

It is also possible to use the equations to estimate the lifetime consequences of improvements or deterioration in mRS. We do this using the following financial costs £137 for an A&E Attendance, £444 for elective bad day and £500 for a non-elective bed day [REF?]. We also assume (based on our data that X% of mRs, y% of mRS are discharged to long term nursing care and 95% of these people remain there for the rest of their lives. Utilities to derive QALYS from life expectancy and mRS (0 = 0.95, 1 = 0.93, 2 = 0.83, 3 = 0.62, 4=0.42, 5 = 0.11 )[[4]](#endnote-4). The cost of an A&E admission calculated as an average of all ‘consultant led’ and ‘non consultant led’ A&E admissions from NHS Reference Costsv. The cost an elective bed day was taken from the literature and inflated to 2021 pricesvi,vii. The cost for a non-elective bed day was assumed to be the cost of an elective bed day with a 20% premium. The cost of a residential day was taken from Unit Costs of Health and Social Care 2021 where an average of the weekly cost of a ‘for profit’ and ‘not for profit’ residential care home for an older person was calculatedvii.

Table 5 Illustrative Estimated QALY Gains and Financial Consequences of improved mRS

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Patient | Old mRS | New mRS | Additional QALYs | Change in Resource Use | Net Benefit |
| Male 73 | 2 | 0 | 2.57 | -225 | 51,192 |
| Female 80 | 4 | 2 | 2.86 | 22,021 | 79,214 |
| Female 65 | 3 | 1 | 4.69 | 10,845 | 104,535 |
| Male 71 | 5 | 2 | 4.72 | 10,605 | 104,966 |
| Female 71 | 4 | 3 | 1.83 | 29,472 | 66,059 |
| Male 80 | 5 | 4 | 0.41 | -10,343 | -2,201 |
| Net Benefit Calculated at £20,000 per QALY and future costs and QALYS are discounted at 3.5%  Negative Changes in Resource Use are extra costs to secondary care providers | | | | | |

A 73-year-old male who previously was discharged with an mRS of 2, now achieves an mRS 0 because of enhanced treatments gains, after discounting, 2.57 QALYs and incurs an extra £225 of secondary care use over their extended life span. This equates to a Net Benefit of £51,192 when QALYS are valued at £20,000. An 80-year-old woman, whose mRs moves from 4 to 2 sees a Net Benefit of £79,214, made up of 2.86 QALYs and £22,021 of reduced future secondary care use.

**Discussion**

Our model produces estimates of life expectancy and secondary care resource use that can be used in economic models. The benefits of treatments like thrombolysis to secondary care provides are consistent with the published evidence base. The Supplementary Material provides Illustrative examples and includes source code in R, Python and VBA for ease of inclusion. Table 5 shows that at current NICE thresholds of £20,000 per QALY most improvements in mRS would be considered cost-effective. The most notable exception being movements from mRS5 to mRS 4, where QALY benefits are offset by increased secondary care use over the life course.

The main strengths of our models are that they a derived from a cohort of patients followed up for 11 years and are straightforward to incorporate into consistent economic models. The use of data gathered outside of randomised control trials means that longer term outcomes are more likely to represent real world settings. Amongst the weaknesses of the model are that the risk equations are based on a set of patients from one locality and one NHS organisation. Whist mortality information was collected from national sources, secondary care usage may be underestimated if patients move out of the locality. Lack of data about the additional risks of mortality associated with different mRS beyond our follow-up means that their maybe biases associated with applying observed additional mortality risk. This is most likely to overestimate the risk of death in younger lower mRS who were most likely to be alive beyond censor. Our models of resource use and associated costs only include secondary care costs. Economic models taking wider perspectives should include information about primary care, social care and informal care costs over the estimated life course.

Future research will include estimates of other resource types derived from linking data about our cohort to other data sources. We will also refine our models of resource use. Whilst the existing models reflect relative differences between mRs, other model forms will be investigated that may better represent absolute levels of resources used.

**Conclusion**

We have successfully developed a set of parametric equations that can be used across economic models of acute stroke care. There use in modelling offers the possibility of increasing the consistency of economic modelling in stroke.

**Supplementary Materials**

**Mortality Prediction**

Form of Gompertz

[1]

Form of Logistic

[2]

Where:

is the probability of death in year 1 (day 365.25)

is the cumulative hazard at time t, where t > 365.25

is the time in days since discharge

is the linear predictor

is the gamma term from the Gompertz function

Predictions

The cumulative probability of death by time t (where t > 365) is

[3]

The probability of death during period t and t+1 is estimated by REF UKPDS

[4]

The method used to calculate a time of death depends on whether the probability for which a time of death is being calculated from is less than the probability of death in year one. If the probability is greater than the probability of death in year one, the time of death based on a probability of death after year one is derived from equation [1], where is the desired death in days is, where the linear predictor is [1]

[5a]

In years

[5b]

Because the probability of death in year 1 is less than the probability of interest, it is necessary to modify equation [5] to allow for the probability of death. p becomes p’ and is given by the equation:

[6]

If the probability of death in year one is greater than the probability of interest, the time of death in days in year one is derived from equation [2] where is the probability of death in year one (from [2]), and the probability of death for which a time is being calculated is . This method is taken from Decision Modelling for Health Economic Evaluation[[5]](#footnote-1).

[7]

Examples:

*Each example uses the coefficients to four decimal places from Table X. As such estimates may be affected by rounding. Full coefficients are reported in the supporting materials.*

For an 80-year-old woman discharged from hospital with a modified Rankin Score of two, her probability of death in the 12 months following discharge would be:

* The logistic linear estimator is -4.2354 + (80-72.8575) · 0.0663 + 1.2590 = -2.50276
* From [2] = **0.0757**

For the same woman, her probability of death by the end of year two would be:

* The Gompertz linear estimator is -9.0670 + [0.00729 · (80-73.7324)] + [0.00059 · (802 - 73.73242)] + [-0.0259 · (80-73.7324)] + 0.41135 = -8.2016
* From [1] = 0.1042
* From [3] = **0.1720**

And her probability of death during year three would be:

* The Gompertz linear estimator as above is -8.3595
* From [1] = 0.2170
* From [3], the cumulative probability of death = 0.2762
* From [4] = **0.0991**

Similarly, a 66-year-old male discharged with a modified Rankin Score of three would have the following probability of death in the 12 months following discharge:

* The logistic linear estimator is -4.2354 + (66-76.4884) · 0.0663 + 2.4773 + 0.2636 = -2.1779
* From [2] = **0.1018**

And the probability of death by the end of two years since discharge:

* The Gompertz linear estimator is -9.067 + [0.00729 · (66-73.7324)] + [0.00059 · (662 - 73.73242)] + [-0.0256 · (66-73.7324)] + 0.68466 + 0.17827= -8.7021
* From [1] = 0.0632
* From [3] = **0.1585**

And during year two

* From [4] and above = **0.0598**

And his probability of death during year three:

* The Gompertz linear estimator as above -8.7021
* From [1] = 0.1316
* From [3], the cumulative probability of death = 0.2255
* From [4] = **0.0648**

To estimate the median time that a 65-year-old man, discharged with a modified Rankin score of two will survive is:

* From [2] check if death more than 50% probability in year 1
* The logistic linear estimator is -4.2354 + (65-72.8575) · 0.0663 + 1.2590 + 0.2636 = -3.2217
* From [2] = **0.0384** which is less than the modelled 0.5
* From [7] with *p* = 0.5
* = 0.4445
* with a Gompertz linear predictor of -9.067 + [0.00729·(65-73.7324)] + [0.00059 · (652 - 73.73242)] + [-0.0259 · (65-73.7324)] + 0.41135 + 0.1782= -9.0323
* = 2724
* To this add 365 as median survival is after year on and divide by 365 to give survival in years
* 2724 + 365 = 3089. 3089/365.25 = **8.46 years**

For a 71-year-old woman, discharged with a modified Rankin score of five, to estimate at what point she will have a 50% chance of still being alive:

* Her probability of death in year one is:
* From [2] 0.5128153 which is greater than 0.5 so use [7], with linear predictor:
* -4.2354 + [0.0663 (71-80.91837)] + 4.9444 = 0.0513
* = 352 days or 0.96 years
* To identify at what point in time there will be a 40% change of her being dead
* = 259 days or 0.71 years

**Resource use prediction**

**Non-elective and elective bed days**

The estimates of the non-elective and elective bed days uses a loglogistic survival model, where the expected number of bed days is:

Where,

ti is the median survival

γ is the ancillary parameter

is the linear predictor

Examples:

*Each example uses the coefficients to four decimal places from Table X. As such estimates may be affected by rounding. Full coefficients are reported in the supporting materials.*

For an 80-year-old woman discharged from hospital with a modified Rankin Score of two, her median survival is 4.43 years. To calculate her expected number of non-elective admission bed days, the linear predictor would be:

* -1.334+(-0.0248\*7.1425)+(0.2966\*1)+(-0.4900) = 1.7048 (to four decimal places)

Therefore, her count of non-elective bed days would be:

Which equals 19.7477 non-elective bed days (to four decimal places)

Similarly, a 66-year-old male discharged with a modified Ranking score of three would have a median survival of 5.88 years. To calculate his expected number of elective admission bed days, the linear predictor would be:

* 1.2735+(-0.0081\*-10.4884)+(-0.0774\*1)+(-0.1613) = 1.1198 (to four decimal places)

Therefore, his count of elective bed days would be:

Which equals 3.4282 elective bed days (to four decimal places)

**A&E Admissions**

The estimates of the number of A&E admissions uses a Weibull accelerated failure-time survival model, where the expected number of A&E admissions is:

Where,

ti is the median survival

γ is the ancillary parameter

is the linear predictor

Examples:

*Each example uses the coefficients to four decimal places from Table X. As such estimates may be affected by rounding. Full coefficients are reported in the supporting materials.*

For a 65-year-old male discharged with a modified Ranking score of two, his median survival time is 8.46 years. To calculate his expected number of A&E admissions, the linear predictor is:

* -0.0692+(-0.0050\*-7.8575)+(0.0791\*1)+(-0.1126) = 0.0832 to four decimal places.

Therefore, his expected count of A&E admissions is:

Which gives an expected count of A&E admissions of 5.3441 (to four decimal places)

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