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Modelling mortality rates for catastrophically injured individuals in Australian and New Zealand injury and disability schemes

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ABSTRACT

Background: It is well established that mortality rates for catastrophically injured participants in injury and disability schemes are higher than those of the general population. However, the extent of this excess mortality within Australian and New Zealand schemes has not previously been quantified. Finity coordinated a collaboration between nine injury and disability schemes across Australia and New Zealand to conduct the first comprehensive trans-Tasman study of mortality for catastrophically injured participants. By pooling data across schemes, this collaboration enabled a larger population to be studied, facilitating deeper and more reliable analysis of mortality experience.

Methods: To develop life tables for impaired lives associated with Traumatic Brain Injury (TBI) and Spinal Cord Injury (SCI) cohorts, we modelled observed mortality rates using a Poisson Generalised Additive Model (GAM). Population mortality rates by age, gender, year and jurisdiction were incorporated as offsets, allowing the model to estimate mortality relative to the general population on the log scale across covariates. The resulting fitted values can be interpreted as covariate-specific Standardised Mortality Ratios (SMRs).

Results: The study quantified mortality outcomes for catastrophically injured individuals by producing SMRs relative to the general population for TBI and SCI cohorts across Australia and New Zealand. The modelling framework revealed substantial variation in excess mortality by age at injury, gender, injury severity, and duration since injury. Consistent with international research, we also found that mortality improvements observed in the general population have not been mirrored in these cohorts. The outputs are SMR tables that can be directly applied in actuarial valuations and premium or levy assessments, providing a robust and context-specific basis for modelling mortality of catastrophically injured participants in Australia and New Zealand.

Keywords: *mortality modelling; traumatic brain injury; spinal cord injury; standardised mortality ratio; generalized additive models*

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BACKGROUND

Finity coordinated a collaboration between nine injury and disability schemes across Australia and New Zealand to conduct a comprehensive trans-Tasman study of mortality for catastrophically injured participants. By pooling data across schemes, this collaboration enabled a larger population to be studied, facilitating deeper and more reliable analysis of mortality experience.

This paper details the methodology and key findings from the study. The results offer valuable insights into mortality rates, serving as an input for projecting future participant numbers and assessing scheme costs.

METHODS

To establish the impaired mortality rate benchmarks, we adopted the following approach:

1 **Review existing research and literature:** We analysed international studies on the mortality of catastrophically injured individuals to ensure our methodology aligned with established industry knowledge and best practice.

2 **Use of standard population mortality rates:** We constructed a historical set of population mortality rates for Australia (by state) and New Zealand, using information published by the Australian Bureau of Statistics (ABS), the Australian Government Actuary (AGA), and Statistics New Zealand. This included applying interpolation and extrapolation techniques for years where mortality rates were unavailable.

3 **Reasonableness checks on scheme data:** Each scheme's dataset underwent checks for completeness, and logical consistency (e.g. accident and death dates, injury type versus severity), with reconciliation to actuarial valuation extracts where possible. We also assessed potential survivorship bias by examining whether datasets captured all known deaths, particularly during periods affected by claims system changes, and applied targeted assumptions to address uncertain death information, or other gaps in historical records where needed.

4 **Data comparison and manipulation across schemes:** Scheme data were compared and adjusted to ensure consistency and comparability across time and between jurisdictions. Adjustments included harmonising field definitions and formats, aligning injury severity classifications, and preparing the data for mortality modelling by calculating appropriate exposure periods and censoring data where required.

5 **Analysis of observed mortality rates using statistical frameworks:** Observed mortality rates across injury and disability schemes in Australia and New Zealand were analysed using a Poisson regression framework. This enabled us to identify key factors influencing mortality experience. Mortality rates were expressed as relativities to population mortality, and sensitivity tests were conducted to assess variability in the results.

LITERATURE REVIEW

Our literature review synthesised existing knowledge on the mortality experience of individuals following TBI and SCI from international studies to inform the methodology and context for this trans-Tasman mortality study.

For TBI, we reviewed 19 peer-reviewed papers published between 2005 and 2022, while for SCI, we reviewed 17 papers published between 2010 and 2020, as shown in Table 1.

Table 1 – Peer-reviewed papers included in the literature review by injury type

Injury type	Reference numbers
TBI	1, 5, 7, 8, 9, 12, 14, 17, 18, 20, 21, 25, 29, 31, 37, 38, 39, 40, 43
SCI	3, 4, 10, 11, 13, 15, 16, 19, 22, 23, 27, 28, 30, 32, 34, 35, 36

The findings are summarised below:

- Studies consistently report that individuals who have experienced TBI or SCI face significantly elevated mortality rates compared to the general population. This is often expressed using Standardised Mortality Ratios (SMRs), which are calculated as the ratio of observed deaths in the study cohort to the expected deaths based on population mortality rates. For example, SMRs for TBI cohorts typically range between 1.8 and 3.2 when compared to age- and gender-matched general population mortality rates.
- Existing research identified the following key predictive factors that influence differences in mortality experience: age, injury severity, gender and time since injury.
- Unlike the general population, where mortality rates have improved over time, studies consistently report no significant improvement in mortality rates for individuals with TBI or SCI. Consequently, SMRs for TBI or SCI cohorts have increased over time as the gap to general population mortality has widened.

While valuable international studies from countries such as Australia, the United States, the United Kingdom and Israel have examined long-term mortality following TBI and SCI, they differ substantially in study design, reference populations, and methodology. As a result, their findings are not always readily comparable or directly applicable to the characteristics of participants covered by Australian and New Zealand injury and disability schemes. A Trans-Tasman mortality study focusing on individuals following TBI and SCI therefore adds important value for the injury and disability schemes.

POPULATION MORTALITY RATES

To benchmark impaired mortality against the general population, we constructed historical population mortality rates for Australia and New Zealand using official life tables.

Australia. Two key sources are available:

- **Australian Bureau of Statistics (ABS)**: annual life tables from 2002-04 to 2021-23, also covering three-year periods. From 2009-11 onwards, ABS tables provide state and territory breakdowns.
- **Australian Government Actuary (AGA)**: Australian Life Tables, published every five years from 1946-48 to 2020-22, based on Census-centred three-year periods.

Both sources publish period mortality rates for males and females, with differences reflecting timing, data sources, and graduation methods. Jurisdictional variation is evident in the ABS tables, with the Northern Territory showing notably higher mortality than other states and territories.

New Zealand. Statistics New Zealand publishes national life tables every five years, covering three-year periods from 1950-52 to 2017-19, separately for males and females.

Constructed series. To create a continuous set of annual population mortality rates by age, gender, year and jurisdiction, we:

- adopted ABS state/territory life tables as the default baseline for Australia,
- assumed each published table applied to the mid-year of its reference period,
- interpolated log-linearly between adjacent tables,
- extrapolated backwards (pre-2009 for Australian states) using historical changes observed in AGA life tables, and
- extrapolated forwards (2023-24 for Australia; post-2019 for NZ) based on pre-COVID five-year average mortality improvements.

This approach provided consistent baselines across jurisdictions, against which SMRs for catastrophically injured participants were calculated.

DATA

We received participant-level datasets from the schemes to review historical mortality experience. Our analysis is based on data available up to 30 June 2024. The data includes individuals who meet the following criteria:

- Injury type: Individuals with TBI, SCI, amputations, burns, or equivalent severe injuries (e.g., brachial plexus injuries)
- Support needs: Individuals expected to require care and support for life
- Scheme inclusion: Individuals who have been formally accepted as participants in a participating scheme.

The Australian schemes in this study cover catastrophic injuries resulting from motor vehicle accidents, whereas New Zealand's ACC covers catastrophic injuries from a broader range of causes, including motor vehicle accidents, sporting injuries and treatment injuries.

To ensure consistency and comparability across schemes and over time, several data manipulations were applied to the datasets provided. These manipulations addressed inconsistencies, standardised formats, and prepared the data for mortality rate analysis. The key steps undertaken were as follows:

- Data standardisation: Harmonised field definitions and formats including dates, injury classifications, and demographic variables such as age and gender. We also converted all datasets to a consistent structure.
- Participant-years: Constructed and limited datasets to relevant 'participant-years' which included calculating appropriate exposure periods commencing from the date of scheme acceptance and censoring data if required.
- Injury severity groups: Segmented datasets by primary injury type (e.g., TBI, SCI, other injuries) and established common severity groupings to ensure comparability across schemes.

Not every scheme uses the same classification system for injury severities, nor provides the same level of detail of completeness.

- For TBI, schemes recorded severity using different scales. These included the Care and Needs Scale (CANS), Functional Code (F-code), Functional Independence Measure (FIM) and Serious Injury Profile. Some of these constructed measures are in turn based on the Glasgow Coma Scale (GCS) and number of days of Post-Traumatic Amnesia (PTA).
- For SCI, schemes provided data on Level of Lesion and ASIA impairment classification, though with varying completeness and granularity.

Given these differences, we established a two-level hierarchy of injury severity groups:

- Level 1 groups were defined to ensure consistency across all schemes by aligning to the most granular comparable data available, aiming for clinical and analytical homogeneity.
- Level 2 groups captured additional granularity beyond Level 1, using own-scheme-specific detail where it was available.

To create these groupings for TBI, we mapped scales where appropriate: FIM scores were aligned to CANS using a clinical approach developed with disability experts, and TAC's F-codes were aligned with CANS using an exposure-based approach. ACC data was retained in its own categories, reflecting its broader coverage of injury causes compared to the Australian motor accident schemes.

For SCI, Level 1 groups were defined by separating participants with incomplete injuries with ASIA D from those classified as ASIA A-C. We note that while the term complete injury is sometimes used clinically to refer only to ASIA A, for the purposes of this study we grouped ASIA A-C together as

complete to maintain consistency across schemes. Within this complete category, further subdivisions were made based on broad lesion location (high quadriplegia, low quadriplegia, and paraplegia).

The resulting Level 1 groupings for TBI and SCI are shown in Tables 2 and 3.

Table 2 – TBI level 1 injury groupings and mapping to scheme-native scales

Level 1 Group	CANS	Fcode	FIM	SI Profile
High	6-7	1-3	18-48	
Medium	4-5	4	49-109	
Low	0-3	5	110+	
ACC High				5
ACC Low				6

Table 3 – SCI level 1 injury groupings

Level 1 Group	ASIA	Level of Lesion
Complete Quad High	ASIA A-C	High quadriplegia (C1-C5)
Complete Quad Low		Low quadriplegia (C6-C8)
Complete Para		Paraplegia (below T1)
Incomplete	ASIC D	

The adjusted datasets allowed us to aggregate scheme information and compare calculated mortality rates with the population mortality baselines developed.

The schemes in New Zealand, Victoria and New South Wales represent the majority of the data, collectively accounting for 96% of participant-years. As such, these three schemes predominantly drive the observed combined mortality experience across Australia and New Zealand.

TBI injuries account for about two-thirds of participant-years, SCI for just under one-third, and 'Other' injuries (e.g., blindness, amputations, burns) comprise a small remainder. Given limited volume and heterogeneity, these 'Other' injuries were excluded from the analysis.

The TBI analysis was conducted on a cohort of 11,786 participants representing a total time exposure of 134,940 participant-years across all participating schemes. Overall, across the combined TBI cohort, 1998 deaths were observed during the study period. Compared to a baseline population expectation of 717 deaths, based on age-, gender-, year- and jurisdiction-matched population life tables. This implies a crude overall SMR of 2.79, meaning, on average, mortality in the TBI cohort is 2.79 times higher than in the general population.

The analysis for participants with SCI encompasses 4,671 individuals, contributing a total time exposure of 58,179 participant-years. Within this combined SCI cohort, 1,155 deaths were observed over the study period. This compares to a baseline population expectation of 375 deaths. The resulting crude overall SMR is 3.08.

MODEL

Mortality analysis involves time-to-event data where risk factors (e.g., attained age, duration since injury) change over time. To handle these time-varying covariates and model mortality rates or SMRs, participant data was restructured into discrete participant-time intervals. Within each short interval, the covariates of interest are constant, allowing analysis of the event count (0 or 1 death) relative to the participant-time exposed. This segmented data structure connects directly to the Poisson regression framework; modelling survival data using finely split time intervals is known to yield a likelihood equivalent to a Poisson regression on the interval counts and exposures. This equivalence allows the powerful and flexible machinery of Generalized Additive Models (GAMs) to be applied to model mortality rates and SMRs.

Within each exposure interval period i, the expected number of deaths, $Y_{\text{expected},i}$, was calculated based on the baseline population mortality rates corresponding to the participant's characteristics. This baseline was determined based on the participant's attained age x, gender, the calendar year (at the start of the interval) and the jurisdiction, using the population life tables.

The observed number of deaths $Y_{\text{actual},i}$ in each person-period i was modelled as an independent realisation from a Poisson distribution:

$$Y_{\text{actual},i} \sim \text{Poisson}(\lambda_i).$$

The Poisson rate λ_i is the product of the expected deaths and the SMR for that period:

$$\lambda_i = Y_{\text{expected},i} \times SMR_i.$$

This relationship is incorporated into the GAM framework using a logarithmic link function and including the logarithm of expected deaths as an offset term:

$$\log(\lambda_i) = \log(Y_{\text{expected},i}) + \eta_i$$

Here, η_i is the linear predictor, representing the logarithm of the SMR ($\eta_i = \log(SMR_i)$).

Covariates were selected based on statistical and actuarial principles, evidence from the literature, and data availability:

- *Continuous covariates*: **Age at Injury**, **Duration Since Injury** and **Calendar Year**. Their effects were modelled using penalized regression splines (specifically, thin-plate regression splines), allowing for flexible, data-driven estimation of potentially non-linear relationships.
- *Categorical covariates*: **Injury Severity** and **Gender**.

The final structure of the linear predictor was:

$$\eta_i = \beta_0 + s_1(AgeAtInjury_i) + s_2(DurationSinceInjury_i) + s_3(CalendarYear) + f_4(InjurySeverity_i) + f_5(Gender_i),$$

where β_0 is the intercept, s_1, s_2 and s_3 are smooth spline functions,
and f_3 and f_4 represent the factor effects. Smoothness and penalty parameters were estimated automatically during fitting using Restricted Maximum Likelihood (REML).

For participants with TBI and SCI, where richer injury detail was available from specific schemes, a two-stage hierarchical modelling approach was adopted to leverage this additional information effectively:

1 **Base model:** A primary GAM model was fitted using the common, broader injury severity groupings available across all participating schemes, estimating a baseline SMR profile (η_{base}).

2 **Refinement model:** A second-stage model introduced an additional term representing the granular injury severity classifications where such detailed information was available. The predicted log-SMR from the base model (η_{base}) was used as an *additional offset* and the structure effectively becomes:

$$\log(\lambda_i) = \log(Y_{\text{expected},i}) + \eta_{\text{base},i} + \eta_{\text{refinement},i}.$$

To provide regularisation, a ridge penalty (L2 penalisation) was applied by specifying this term using the random effect basis. This approach shrinks the coefficients for different levels towards a common mean, improving stability and preventing overfitting, especially where data within specific categories might be sparse.

This allowed the analysis to leverage the full dataset for estimating the overall shape related to common factors, while refining these estimates using more detailed information where available, quantifying the additional mortality impact associated with specific functional scores or injury classifications within the broader TBI or SCI categories.

The exponentiated components of the fitted linear predictor, $\exp(\eta_i)$, provide estimates of the SMR.

Prior to finalising this specification, the model structure was validated using a participant-level 70/30 train-test split. Performance on the testing set was assessed, primarily using actual versus modelled plots across key dimensions, to confirm the model adequately captured the observed mortality patterns and to highlight any potential unmodelled effects.

Alternative specifications and covariates were also explored as part of this process. Models using attained age instead of age at injury, and specifications including gender interactions, were trialled but not adopted due to counter-intuitive shapes or limited improvement in fit. We further examined factors such as scheme, geographic location, socio-economic status and Indigenous status. These checks revealed some residual patterns. For example, lower than expected mortality in metropolitan areas for SCI, lower than modelled mortality in the most advantaged socio-economic decile, and higher relative mortality for Indigenous participants (particularly in SCI).

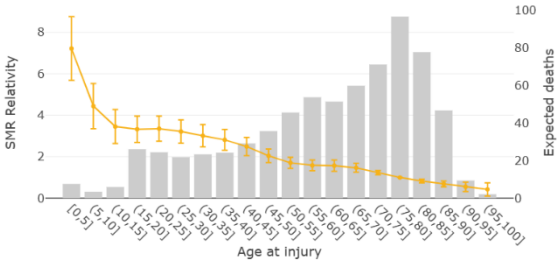
While noteworthy, these effects were subject to limited data and were therefore not incorporated into the final specification. The chosen model was judged to provide the best balance between interpretability, robustness and applicability for scheme valuations.

RESULTS

Traumatic brain injury (TBI)

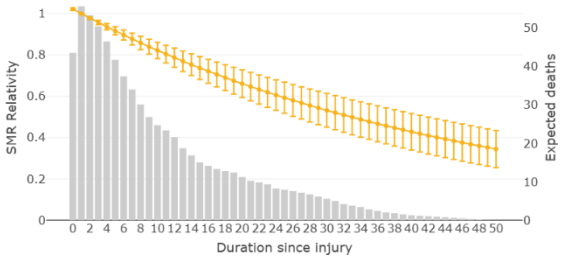
Figures 1 to 5 display the estimated effects (exponentiated coefficients or smooths, representing SMR relativities) for the covariates included in the base model. Figure 6 illustrates the relativities estimated from the second-stage refinement model for the granular injury severity classifications. For each factor, the baseline relativity (SMR = 1.0) is set at the category or point with the largest exposure (in terms of expected deaths), as indicated by the grey bars representing expected deaths on the secondary, right-hand side, axis.

Figure 1 – TBI SMR relativities at age at injury



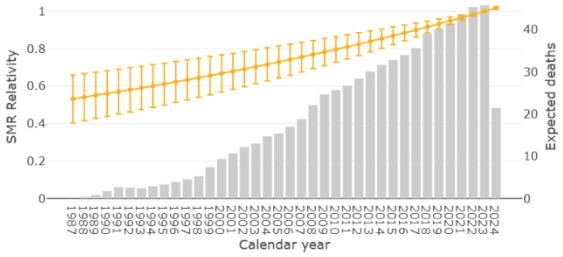
We observe a decreasing relationship between age at injury and subsequent mortality risk relative to the general population.

Figure 2 – TBI SMR relativities for duration since injury



The relative mortality risk is highest immediately following the injury and decreases with duration. The first-year post-injury results should be interpreted with caution. Our analysis includes only individuals accepted into participating schemes, so it does not capture the immediate post-injury mortality risk, and differences in scheme operational processes and acceptance timing may influence when individuals first enter the dataset. The modelled SMR relativity for the first-year post-injury therefore reflects the average experience across schemes.

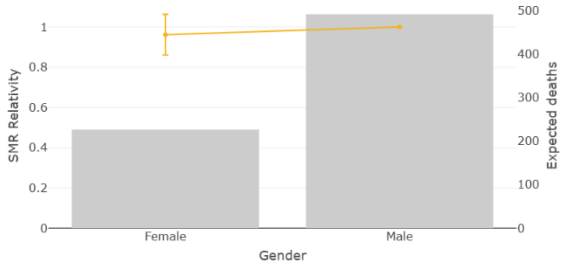
Figure 3 – TBI SMR relativities for calendar year



A clear, steady upward trend is observed in excess mortality risk across the study period, spanning from the late 1980s to the early 2020s.

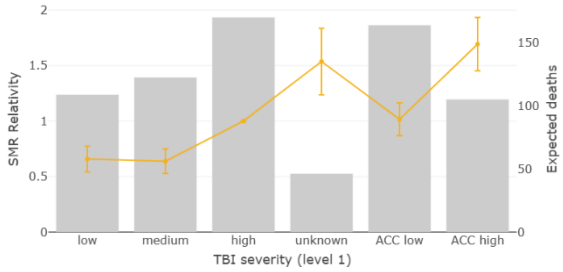
This trend indicates that mortality improvements seen in the general population over recent decades have not been experienced to the same extent by the traumatic brain injury (TBI) cohort.

Figure 4 – TBI SMR relativities for gender



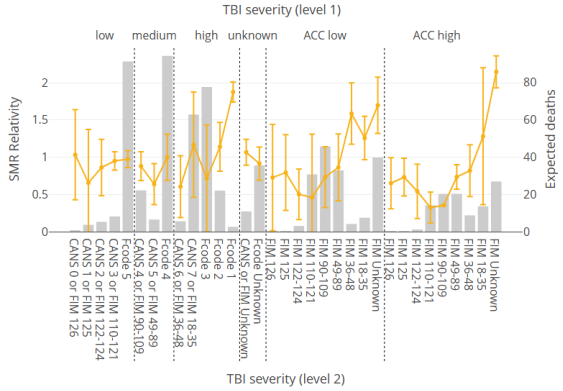
Females are associated with a slightly lower excess mortality risk compared to males, after adjusting for other factors, albeit not statistically significant.

Figure 5 – TBI SMR relativities for TBI injury severity group



There is a clear trend observed associated with injury severity. Using the High severity category as the baseline, the Low and Medium groups show substantially lower and broadly similar risks. For the ACC scheme, the same contrast is evident, with the High group noticeably higher than the Low group, which is comparable in risk to the Australian High category.

Figure 6 – TBI SMR relativities for Level 2 refinements within Level 1 injury severity groups; relativities are conditional on and do not include Level 1 effect



The hierarchical model refines the SMR estimates using more detailed injury classifications: CANS, FIM (ACC, MAIB) and F-codes (TAC). These relativities act as multiplicative adjustments on top of the base model, with values above 1.0 indicating higher, and below 1.0 lower, mortality risk than predicted *within* their Level 1 category.

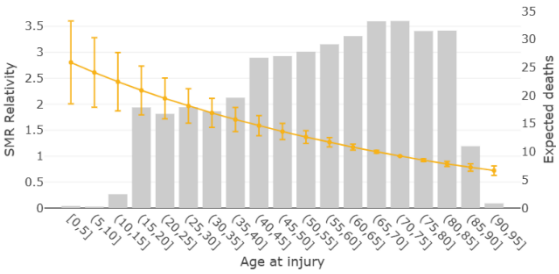
Across schemes, some clear patterns emerge. Within ACC, relativities generally increase with higher FIM, though data sparsity at lower levels and wide confidence intervals create greater uncertainty. A similar upward gradient is seen in the low-to-high range for CANS/FIM, while TAC's F-codes 1-3 show the expected increase as level of function decreases.

When combining the Level 2 refinements with the Level 1 base estimates, manual adjustments can be applied in cases where data are particularly sparse and confidence intervals very wide. These adjustments serve as guardrails to enforce a consistent monotonic progression, avoiding spurious deviations while preserving the overall shape indicated by the data.

Spinal cord injury (SCI)

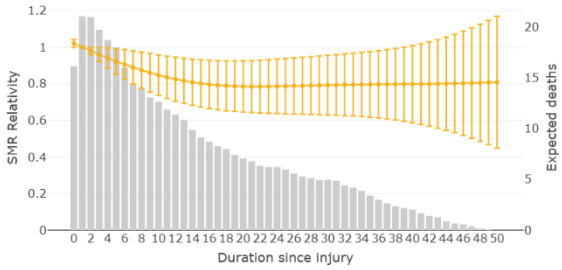
Figures 7 through 11 present the estimated partial effects for the primary covariates in the base model, while Figure 12 displays the relativities from the second-stage refinement based on granular injury classifications.

Figure 7 – SCI SMR relativities for age at injury



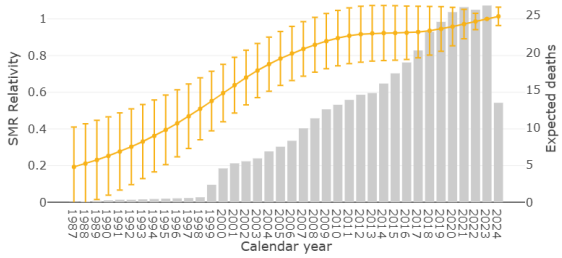
The SMR relativity decreases progressively as age at injury increases.

Figure 8 – SCI SMR relativities for duration since injury



Relativities are highest in the early years following injury and decline steadily over the next 15 years before stabilising. As for TBI, the first-year post-injury SMR should be interpreted with caution, as it reflects the average post-acceptance experience across schemes, which may differ in their processes and timing.

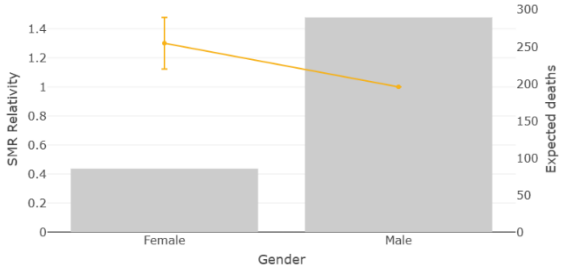
Figure 9 – SCI SMR relativities for calendar year



SMR relativity increasing markedly over calendar year, indicating mortality improvements within this cohort lagged behind the general population.

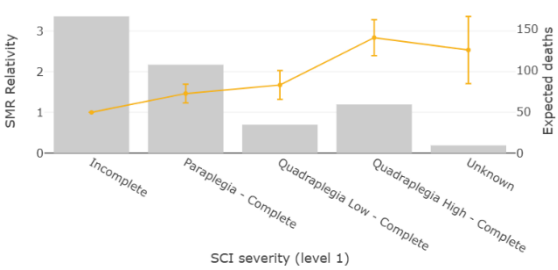
Although the early rise is steep, it occurs in a data-sparse period and levels into a more gradual upward trend from the 2000s onward.

Figure 10 – SCI SMR relativities for gender



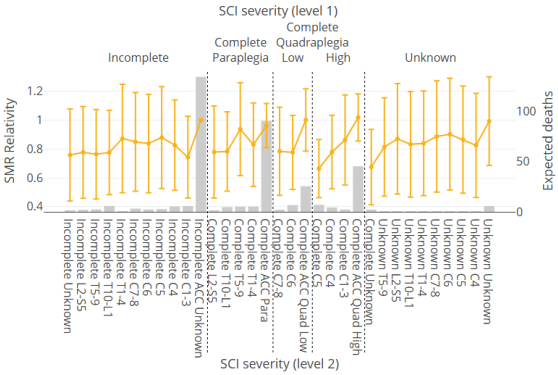
Females with SCI experience a higher excess mortality risk than males, and this difference appears statistically significant.

Figure 11 – SCI SMR relativities for SCI injury severity group



Mortality risk increases with SCI severity, with incomplete injuries showing the lowest risk, followed by complete paraplegia and then low-level complete quadriplegia, and peaking for high-level complete quadriplegia.

Figure 12 – SCI SMR relativities for Level 2 refinements within Level 1 injury severity groups; relativities are conditional on and do not include Level 1 effect



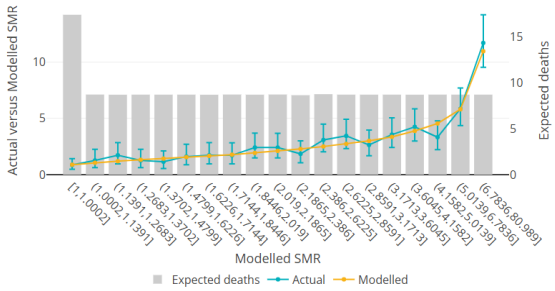
The hierarchical model further refines the SMR estimates using detailed level of lesion information where available. Most SCI data come from ACC, which does not include level of lesion, and these groups tend to show the highest relativities within each severity band. For schemes with this data available, no consistent pattern emerges across level of lesion within level 1 SCI severities except for high-level complete quadriplegia where the estimates suggest higher risk for C1-3 injuries compared to C4 and C5.

GOODNESS OF FIT

To assess how well the refined model structure captures the observed mortality patterns, goodness-of-fit analyses were conducted on the test (holdout) data set. A key diagnostic is the comparison of Actual versus Modelled (AvM) across different dimensions. Figures 13 and 14 present the

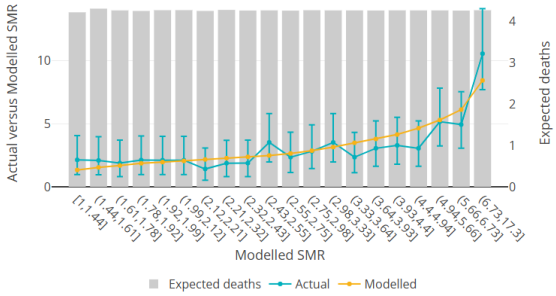
AvM plot by the modelled SMR, grouped in 20 bins by (roughly) equal amount of baseline expected deaths. The AvM plot compares the actual observed SMR (blue line, calculated as $\sum_i Y_{\text{actual},i} / \sum_i Y_{\text{expected},i}$, with one-way confidence intervals) against the modelled SMR (yellow line, calculated as $\sum_i \lambda_i / \sum_i Y_{\text{expected},i}$) within each bin of modelled SMR ranges. The grey bars indicate the exposure, i.e. the baseline expected deaths ($\sum_i Y_{\text{expected},i}$).

Figure 13 – Actual versus modelled by the modelled SMR for the Test TBI data set.



The model appears well-calibrated overall with the modelled SMR (yellow line) generally tracking the observed SMR (blue line) across the range of modelled SMR, suggesting the model adequately captures the magnitude and variation in excess mortality risk.

Figure 14 – Actual versus modelled by the modelled SMR for the Test SCI data set.



The plot indicates a generally reasonable calibration with the modelled SMR (yellow line) tracking the observed SMR (blue line) across most of the risk spectrum. Note however the smaller data volume of SCI compared to TBI resulting only in a Test data set with 85 baseline expected deaths to rely on for validation purposes, resulting in wider confidence intervals.

SENSITIVITY ANALYSIS

Several sensitivity analyses were conducted to assess the robustness of the SMR modelling results. We investigated the sensitivity of the results with respect to:

- **The choice of population life tables**:
  - *National ABS life tables*: Replacing the state-specific tables for Australia with the national Australian life tables.
  - *AGA life tables*: Replacing the state-specific tables for Australia with the AGA Australian Life Tables.
- **Exclusion of New Zealand data (ACC):** Assessing the impact of focusing solely on the Australian schemes
- **Time Period**: Restricting the analysis to data up to 2019, i.e. excluding the COVID period.

The sensitivity analyses revealed that while the overall SMR level could change minimally depending on the scenario, the core patterns of SMR relativities across covariates like age, duration, calendar year and severity were consistent with the main analysis.

CONCLUSION

This study combined data from Australia and New Zealand, creating a comprehensive dataset that enabled analysis of mortality outcomes for individuals with TBI and SCI.

As an output from this study, we have created a set of SMR tables based on the experience across all participating schemes and our research. The results of this study are a vital input for participating schemes to develop scheme-specific mortality assumptions for the purposes of estimating the development of participant numbers.

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- Lifetime Care and Support Scheme (New South Wales, Australia)
- Lifetime Support Authority (South Australia, Australia)
- Motor Accident Compensation Commission (Northern Territory, Australia)
- Motor Accidents Insurance Board (Tasmania, Australia)
- National Injury Insurance Scheme (Queensland, Australia)
- Transport Accident Commission (Victoria, Australia)

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RELIANCES AND LIMITATIONS

Citation

Readers using these results in their work are asked to cite this paper as:

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This paper is provided for the sole purpose of documenting the findings of a mortality study specific to catastrophic injuries accepted into participating schemes. It is not intended, or necessarily suitable, for any other purpose.

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Data Provided

We relied on the completeness and accuracy of the information we received. If the information provided to us is inaccurate or incomplete, it may invalidate our findings.

We did not audit or verify the information provided to us but have reviewed it for general reasonableness and consistency.

We have relied on the injury severity information provided which we understand is based on the latest information available to each scheme. Experience indicates that the injury severity particularly for brain injuries can change over time and this has not been modelled in this mortality study.

Uncertainty

It is not possible to estimate mortality rates with certainty. Differences between actual experience and our estimates are normal and to be expected.

Many things may change in the future. We have formed our views based on the current environment and what we know today based on the historical mortality experience

observed in the participant schemes. If future circumstances change, it is possible that our findings may not prove to be correct.

As well as difficulties caused by limitations on the historical information, outcomes remain dependent on future events, including but not limited to legislative, social, technological, medical and economic forces. We have generally assumed that future mortality experience will proceed as in the recent past, and we have not anticipated any extraordinary changes to the environment that might affect the future mortality experience of participants. It is quite possible that one or more changes to the environment e.g. improvements in treatment of injures could produce an outcome materially different from our estimates.

While we have made assessments that we consider to be reasonable, it is impossible to estimate any direct impacts of COVID-19 on recent mortality experience with any level of certainty.

The mortality experience for the first-year post-injury must be interpreted carefully as each scheme will have differences in their operational policies and processes that affect the speed of participants accepted into the scheme. The modelled SMR for the first-year post-injury relate to the average experience of all schemes.

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