Association between trauma severity models and opportunities for improvement: A retrospective cohort study

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2 Introduction

Management of severe trauma is highly time-sensitive intervention that is dependent on the actions of a chain of healthcare providers spanning multiple professions and disciplines. Outcomes in severe trauma are dependent on the quality of care received (1), and errors in management are a common cause of preventable deaths (2–4). Since mistakes by any one provider can lead to severe outcomes, attempts to improve trauma outcomes must seek to improve all aspects of the entire chain of care. This can only be achieved through peer review and consequently, morbidity and mortality (M&M) review is the cornerstone of all modern trauma quality improvement (QI) programs. The purpose of M&M review is to evaluate selected patient cases, establish whether there was opportunity for improvement (OFI), and implement corrective actions.

The WHO recommends that all "deaths, complications, adverse events and errors" should be reviewed (5) at M&M conferences. One of the drawbacks of M&M review is the process of identifying which cases should be reviewed. Urban trauma centres experience large caseloads and the time resource burden of reviewing even just fatalities can be considerable. The process of evaluating cases to determine which cases should be reviewed is also a time-consuming process. Due to this, many trauma centres have use audit filters that automatically flag cases for review. The potential benefits of this are twofold: it reduces the resource burden of case selection, and effective audit filters may help to identify the cases most likely to have been mismanaged.

One proposed audit filter, that is already used in many hospitals, is the use of trauma severity models that estimate the probability of survival. The focus There are many trauma severity models and the choice of model may be dependent on the region, as these algorithms tend to perform best when used in populations similar to the one the model was developed from. TRISS, an American model, is the most commonly used model worldwide (6). The British model PS is commonly used in the UK and Europe (7). NORMIT, a Norwegian model, was validated and found to have good performance in a Swedish trauma centre but was less-suited when applied to a national population (8).

One use case for severity models as audit filters is choosing to only review fatalities where the estimated probability of survival was high. The assumption in this case is that unexpected deaths are more likely to have OFI, and a fatality where OFI is found is a preventable death. Two studies have examined this assumption by investigating whether trauma severity models can predict preventable deaths. A 2016 study found that neither TRISS nor PS reliably predicted preventable deaths in a major trauma centre in London (9). Another study in 2019 found that NORMIT and TRISS performed poorly at predicting preventable and non-preventable deaths at a Scandinavian level-I centre (2).

These studies indicate that trauma severity models are of limited use in improving case selection with regards to fatalities. However, to date there have been no studies that examined whether trauma severity models can predict OFI across the board and not just in fatalities. The aim of this study is to evaluate how the trauma severity models TRISS, NORMIT and PS are associated with, and to what extent they can predict OFI.

3 Methods

3.1 Study design

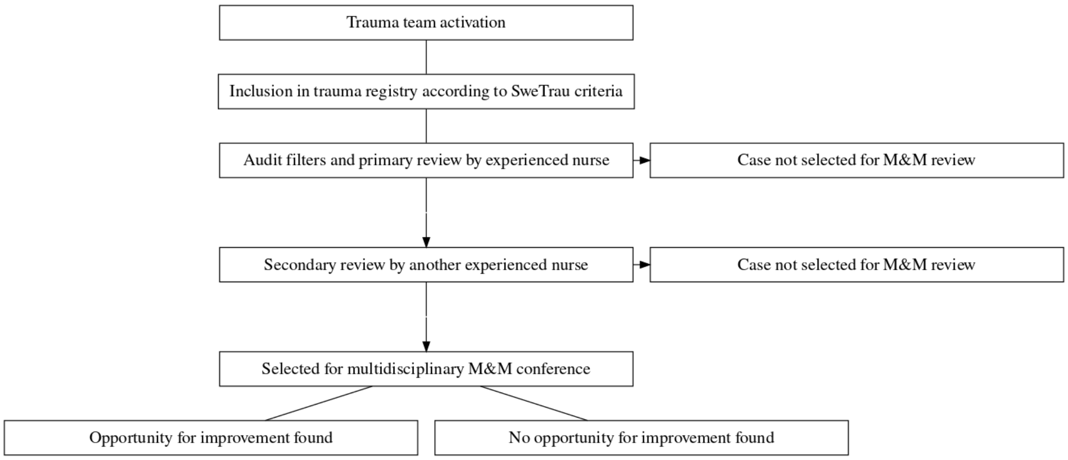
This is a single-centre retrospective cohort study that uses data from two registries at Karolinska University Hospital in Stockholm, Sweden: the trauma registry and the trauma care quality database. The trauma care quality database is a subset of the trauma registry and contains data on trauma patients who were selected for M&M reviews. These two databases were linked and then analysed to estimate the association between the common trauma severity models TRISS and NORMIT and OFI using logistic regression. The predictive performance of these models was evaluated using measures of discrimination and calibration.

3.2 Setting

The trauma centre at Karolinska University Hospital is equivalent to a level 1 trauma centre according to American College of Surgeons standards and has a catchment population of almost 3 million residents (10) .

The trauma registry at Karolinska University Hospital is part of SweTrau, Sweden's national trauma registry, and uses the Utstein template. All trauma patients meeting the SweTrau inclusion criteria are registered in the trauma registry by research nurses at the trauma centre. Data is collected from the patient's electronic medical records.

M&M conferences are held at Karolinska University Hospital ten times per year and are attended by all involved specialities and professions. Each case reviewed is registered in the trauma care quality register with data about the outcome of the review. At Karolinska University Hospital, all fatalities are automatically selected for M&M review. In addition to this, the electronic medical records of all trauma patients are screened by research nursing staff to identify cases that potentially received sub-optimal care. These nurses also use audit filters that automatically highlight cases with abnormal parameters. Cases that two research nurses have evaluated and found to have potential for sub-optimal care are also selected for M&M review. Figure 1 gives an overview of the workflow that leads to determination of OFI.



3.3 Participants

We retrospectively analysed patient registries that cover a seven year period, from 2014 to 2021. Participants were patients >15 years of age who were alive on arrival at hospital that were both registered in the trauma registry and also had a recorded outcome of an M&M review. We excluded patients where registry data was lacking that was necessary to calculate trauma scores.

Included in the trauma registry are all patients for whom the trauma team was activated after a potentially traumatic injury, regardless of trauma score, and all patients with a NISS >15 regardless of whether the trauma team was activated. Patients where the only traumatic injury is a chronic subdural haematoma and patients for whom the trauma team was activated without an underlying traumatic injury are excluded.

3.4 Variables

3.4.1 Outcome

The studied outcome is the binary variable “opportunities for improvement” (OFI), as identified by M&M reviewe at Karolinska University Hospital. OFI is registered in the trauma care quality database and is coded as either “Yes - at least one opportunity for improvement identified” or “No - no opportunities for improvement identified.”

3.4.2 Exposures

The exposures of interest were the trauma severity models TRISS, NORMIT, and PS. Variables taken from the registry were age, gender, mechanism of injury, Injury Severity Score (ISS), New Injury Severity Score (NISS), Glasgow Coma Scale (GCS), respiratory rate and systolic blood pressure. Conversion and handling of these variables was carried out according to the SweTrau manual.

The Revised Trauma Score (RTS) was calculated according to the original published algorithm (11). We chose to use the PS12 algorithm instead of the newer PS19 model due to our registry lacking data needed to calculate PS19 (12). NORMIT was calculated using the revised 2018 coefficients (13). TRISS was calculated using the revised 2009 coefficients (14). In order to avoid excluding patients who were intubated pre-hospitally, the pre-hospital GCS value was used when calculating TRISS for patients who were intubated before arrival at hospital.

3.5 Bias

The code for data analysis was written by a student researcher using simulated data to reduce the risk of researcher bias. Real-world data was only used once the data analysis model was completed and found to work correctly on simulated data.

3.6 Statistical methods

The statistical programming language R was used for data collection and analysis (15). Logistic regression was used to estimate association between the estimates of the trauma severity models and OFI and the effect size was given as the derived OR. The CI for the OR was computed using the Wald estimator. Receiver operator characteristic (ROC) curves were used to assess diagnostic performance. The area under the curve (AUC) was calculated to compare the models with one another. The Integrated Calibration Index (ICI) was used to measure calibration. Accuracy was plotted and is reported as accuracy at a >=0.5 cutoff . Confidence intervals for the AUC, ICI and accuracy were computed with 1000 stratified bootstrap replicates. Results are presented with a confidence interval of 95%. A p-value of <0.05 was considered significant.

4 Results

5 Discussion

6 Conclusion

7 References

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