Transferability of clinical prediction models for early trauma care

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**Background:** Trauma results in approximately 3,8 million deaths annually. Clinical prediction models are often used for triage in early trauma care. Previous research has indicated transferring these models between different settings might adversely affect model performance.

**Methods:** Patients age 15 or above registered between the years 2011 and 2016 in the Swedish national trauma registry SweTrau were included. Three sets of data were created: High and low volume centres, metropolitan and non-metropolitan centres, and multi and single centres. Clinical prediction models were developed using logistic regression in each data set and transferred within sets. Model performance was evaluated in all data sets using mistriage rate, undertriage rate and overtriage rate. Multiple imputation using chained equation was used to handle missing data. Model performance was reported as medians with 95% uncertainty interval across imputed data sets.

**Results:** 27043 patients were included. Model validation mistriage rate ranged from 0.200 (0.190 - 0.380) to 0.530 (0.420 - 0.630), and transferred model mistriage rate ranged from 0.190 (0.130 - 0.840) to 0.550 (0.200 - 0.800) across all samples. Performance after transfer when compared to receiving sample validation performance resulted in subtantial uncertainty in all samples. Worst performance after transfer was found in the metropolitan sample with a mistriage difference of 0.300 (-0.080 - 0.640).

**Conclusions:** In all samples model transfer was associated with high levels of uncertainty. Notably, transfer from the metropolitan sample to the other sample in the data set lead to an increased mistriage rate, primarily due to increased overtriage.

**Keywords:** Trauma, Clinical prediction model, Transferability, Mistriage, Undertriage, Overtriage

# Introduction

Trauma, defined as physical injuries to a host by outside objects [1], results in approximately 458.5 million cases anually across the globe [2], and an estimated 3.8 million deaths [3, 4]. Each year, 9% of the world’s deaths are the result of trauma, with the leading causes being road traffic accidents, suicide, and homicide. Predictions indicate the incidence of these causes is likely to increase by 2030 [5].

In a typical, high-resource setting, the initial management of trauma is performed on the scene by Emergency Medical Services (EMS). Patient data and vital signs are transferred to the receiving hospital. This information is then evaluated using a system to determine the level of trauma, prepare adequate resources [6] and dictate if a full or limited trauma team is activated [7].

Systems that determine the level of trauma during early trauma care can be based on clinical prediction models. Models differ in quality and characteristics, but generally perform well at predicting survival [8]. Many models are developed in a single, standardized context, such as a major trauma centre but are then implemented in different context, such as non-trauma centres.

What is not fully understood is how this transfer affects model performance. Previous research has shown that model performance in terms of calibration can be adversely affected [9]. However, the aforementioned research studied model transfers between substantially different settings and did not assess more clinically relevant performance measures, such as misclassification.

In trauma, misclassification is often referred to as mistriage. Triage refers to the classification of severity as minor or major trauma. Mistriage can be subdivided into overtriage, the incorrect classification of a patient with minor trauma as major trauma, or undertriage, the incorrect classification of a patient with major trauma as minor trauma. Mistriage can ultimatly lead to decreased patient survival, and is also detrimental to patient care and distribution of resources [7].

Thus, the effect of model transfers between care contexts within a single healthcare system, as well as the effect of such transfers on mistriage, have not been studied and represent substantial knowledge gaps. The aim of this study is to assess how transfers of clinical prediction models for early trauma care between different care contexts within a single health system affect mistriage rates.

# Materials and methods

## Study design

A registry-based cohort study was conducted. Sweden has a nationally encompassing trauma register called SweTrau. SweTrau data was used to create clinical prediction models, which were transferred between different care contexts to study the effects on mistriage. The study and analysis plans were made publicly available before the research was undertaken [10].

## Setting

In Sweden, trauma is the most common cause of death before 44 years of age, and 10% of major trauma patients suffer some form of disability. The societal effects of trauma are substantial, with the loss of work days comparable to those lost from cardiovascular and malignant diseases combined [11].

Trauma care in Sweden is usually clearly defined in major metropolitan areas: trauma patients are transported directly to a predesignated hospital with specific trauma competency. In more rural parts of the country, trauma patients are instead transported to the nearest hospital for stabilization. Once stabilized, they may then be transported to hospitals with more advanced trauma care capacity [12]. Most hospitals in Sweden use some form of system to categorize the level of trauma, usually based on patient vital signs and injury mechanism, as reported by the EMS, or as registered in the emergency department [13].

Today, 52 of the 55 Swedish hospitals record trauma cases in SweTrau. Currently, the registry includes 55 000 cases, and its use is encouraged in both academic research and local quality improvement initiatives [14].

## Participants

The eligibility criteria were adult patients aged 15 years or above registered in SweTrau between 2011 and 2016. The study aimed to assess adult trauma and not paediatric trauma which differs in physiology, triage and initial care [15]. The Swedish guidelines for trauma activation define children as age <15 [13].

## Variables

### Participant characteristics

To describe the patient cohort we reported age, sex, Injury Severity Score (ISS) and New ISS (NISS).

### Model predictors

The clinical prediction models used the predictors systolic blood pressure (SBP), respiratory rate (RR) and Glasgow coma scale (GCS), all on arrival to hospital. The rationale for these three predictors is that they are part of multiple established clinical prediction models for early trauma care, such as the Revised Trauma Score [16].

### Model outcome

The outcome used to develop the clinical prediction models was all cause mortality within 30 days of trauma.

### Study outcome

ISS > 15 was used as the gold standard to define trauma severity as major trauma, and hence patients with ISS ≤ 15 were considered minor trauma [17]. Overtriage was defined as the event when a clinical prediction model classified a patient with ISS ≤ 15 as major trauma, and undertriage as the event when a clinical prediction model classified a patient with ISS > 15 as minor trauma. Overtriage rate was defined as the number of overtriaged patients divided by all patients. Undertriage rate was defined as the number of undertriaged patients divided by all patients. Mistriage rate was defined as the sum of the over- and undertriage rates.

## Data sources and measurements

Model predictors, outcome, participant characteristics and study outcome as outlined above were all obtained from SweTrau. The method of measurement for the model predictors is not specified in the registry entries. In Swedish emergency rooms, patient parameters are usually obtained by a registered nurse or assistant nurse and are assumed to be accurate. Whether the patient is dead or alive 30 days after trauma is manually entered into the registry by each respective hospital. NISS and ISS are calculated by hospital personnel based on the patient’s injuries.

## Bias

Data analysis was conducted according to a prearranged analysis plan. The analysis plan and statistical analysis code was finalised using simulated data. These efforts were taken to avoid confirmation bias. The analysis plan was reviewed by an experienced statistician and programmer prior to implementation. Neither the outcome nor variables were blinded when during analysis, which made a structured approach important to ensure objectivity.

## Study size

All patients matching eligibility criteria were included. Four data sets were used to study the transfer of clinical prediction models, each data set representing a different care context. The data sets, and sample size considerations are outlined below.

## Quantitative variables

GCS was modelled as a continuous linear term, and SBP and RR were modelled using restricted cubic splines with four knots whenever possible, placed at equally spaced percentiles. When describing the participant characteristics, quantitative variables were presented as continuous. ISS was presented as dichotomous using ISS > 15 as the cutoff.

## Statistical methods

### Data sets

The complete SweTrau cohort was split into three overlapping sets of data, each representing a plausible care context for model transfer. These data sets were further divided into samples:

### Data set 1: High and low volume centres

Two samples were derived from the SweTrau cohort, based on the number of patients. High volume centres were those within the top quartile of number of patients received. The rest were low volume centres.

### Data set 2: Metropolitan and non-metropolitan centres

This data set was also split into two samples: a metropolitan sample consisting of patients from greater Stockholm, greater Gothenburg and greater Malmö, as defined by statistics Sweden, and a second sample of patients from non-metropolitan areas.

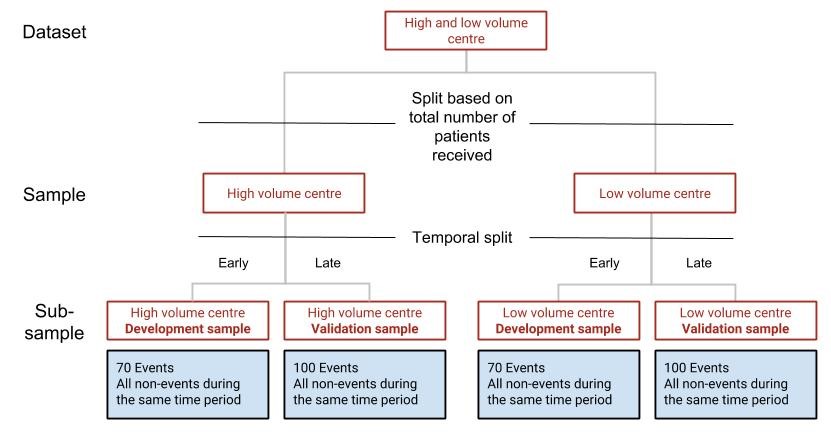
### Data set 3: Multi- and single centre data

In this data set, two samples were created. One centre with a large enough sample size to develop and validate a model was its own sample. The multicentre sample consisted of the combined data from all centres.

A fourth dataset was initially created, consisting of individual centres that had a large enough sample size to develop and validate a model. However, this data set was removed before analysis due to a lack of centres with a large enough sample size.

### Development and validation sample

The samples in each data set were split into two subsamples using a temporal split based on the date of trauma. The earlier subsample was the development sample, and the later subsample the validation sample. The development sample contained 70 events (events being patients who died within 30 days of the trauma) and all non-events (non-events being patient survival 30 days past the trauma) during the same time. The rationale for including 70 events is that at least 10 events per free parameter were needed in the logistic regression to obtain stable coefficient estimates [18]. The validation sample contained 100 events and at least 100 non-events, which was suggested as the minimum number by Vergouwe in 2005 for external validation samples [19]. Figure 1 shows the development of the samples using the high- and low volume centre data set as an example. The minimum sample size of development and validation samples were 140 and 200 respectively. We performed analyses only on data sets for which all samples included at least the minimum sample size.

  
**Fig. 1: Sample development in the high and low volume centre data set.** Initial split based on number of patients. Temporal split made using date of traumatic event.

### Sequence of analysis

The programming language R was used for all analyses [20], and all code has been made publicly available [10]. Analyses were performed in the sequence of model development, model validation and finally model comparison. These steps were repeated in each data set. Below, we use the transfer of a model from the high volume centre sample to a low volume centre sample as an example to describe the complete procedure.

### Model development

In the model development step, a clinical prediction model was developed in the high volume centre development sample. The model was developed using logistic regression. The dependent variable was all-cause mortality within 30 days of trauma and the independent variables SBP, RR, and GCS were modelled as previously described. To avoid overfitting the model, a bootstrap procedure was used to estimate a linear shrinkage factor that was then applied to the model coefficients [21]. The shrunk model was used to estimate the probability of all-cause 30-day mortality in the development sample. A gridsearch was performed across estimated probabilities in the development sample to identify the cut-off that optimised overtriage keeping undertriage at less than 5% [22]. This cut-off was then used to classify patients as major or minor trauma.

### Model validation

In the model validation step, the model performance was assessed in the high volume centre validation sample and in the low volume centre validation sample. First, the model was used to estimate the probability of all-cause 30-day mortality in each sample. Then the probability cut-off identified in the development sample was applied to the validation samples, patients were classified as major or minor trauma, and model performance was estimated.

### Model comparison

Finally, the difference in model performance between the high and low volume centre validation samples was calculated. Empirical bootstrap was used to estimate 95% confidence intervals (CI) around performance and differences in performance estimates. Both bootstrap procedures used 1 000 bootstrap samples drawn with replacement of the same size as the original samples. The three steps of model development, model validation, and model comparison were repeated in all four sets of data.

### Performance measures

Model performance was assessed in terms of over-, under-, and mistriage rates as defined above.

### Missing data

We used multiple imputation using chained equations (mice) to handle missing data [23]. The number of imputations created for each data set was equal to the highest percentage of missing data in that data set. Quantitative variables were imputed using predictive mean matching and qualitative variables were imputed using logistic regression. SBP and RR was transformed as restricted cubic splines before imputation. All analyses outlined above were then conducted separately in each imputed dataset. We present the combined results as the median point estimate across imputations along with an empirical bootstrap of the 25th and 75th percentiles across imputations, i.e. the lower bound of the presented interval is the lower bound of a 95% CI of the 25th percentile and the upper bound is the upper bound of a 95% CI of the 75th percentile. This combined CI was referred to as an Uncertainty Interval (UI) and was used to express the added uncertainty associated with the imputation procedure to handle missing data; as such, it is more conservative than a standard 95% CI.

## Ethical considerations

The study was approved by the regional ethics review board in Stockholm, Sweden. Ethical review numbers are 2015/426-31 and 2016/461-32. All patients in SweTrau had received letters detailing their inclusion in the database, and the possibility of their data being used for scientific purposes. It was assumed that the patients who consented to the use of their SweTrau data for research want to contribute to the improvement of care, and thus by performing this study the authors hope to honour their wishes.

# Results

We analysed data from 27043 trauma patients to investigate the effects of transfer on clinical prediction models (Table 1). The total number of missing observations across all variables was 10046 in the entire study cohort. The sample with the highest percentage of missing observations was the non metropolitan sample with 48% incomplete observations. The variable with the highest number of missing values was ed\_rr\_value, with 8337 missing values, or 31% of the total values for this variable. The percentages of missing values for the other model predictors, was 8% for GCS and 9% for SBP.

**Table 1. Sample characteristics of multiple imputed data.** Data is presented as medians with interquartile range (IQR) or counts with % as applicable.

|  |  |  |  |
| --- | --- | --- | --- |
| characteristic | level | high volume | low volume |
| n (%) |  | 20042 (1.7) | 7001 (0.6) |
| Age (median [IQR]) |  | 40.0 [25.0, 57.0] | 46.0 [27.0, 64.0] |
| Gender (%) | Male | 13146.7 (65.6) | 4710.2 (67.3) |
|  | Female | 6895.3 (34.4) | 2290.8 (32.7) |
| GCS (median [IQR]) |  | 15.0 [15.0, 15.0] | 15.0 [14.0, 15.0] |
| SBP (median [IQR]) |  | 139.0 [125.0, 153.0] | 137.0 [120.0, 153.0] |
| RR (median [IQR]) |  | 18.0 [15.0, 20.0] | 18.0 [16.0, 22.0] |
| 30d survival (%) | Alive | 19291.8 (96.3) | 6611.6 (94.4) |
|  | Dead | 750.2 (3.7) | 389.4 (5.6) |
| ISS (median [IQR]) |  | 3.0 [1.0, 9.0] | 5.0 [1.0, 13.0] |
| NISS (median [IQR]) |  | 3.0 [1.0, 12.0] | 6.0 [1.0, 17.0] |
| ISS>15 (%) | Yes | 2678.2 (13.4) | 1432.4 (20.5) |
|  | No | 17363.8 (86.6) | 5568.6 (79.5) |

|  |  |  |  |
| --- | --- | --- | --- |
| characteristic | level | metropolitan | non metropolitan |
| n (%) |  | 13043 (1.0) | 14000 (1.1) |
| Age (median [IQR]) |  | 41.0 [26.0, 58.0] | 42.0 [25.0, 60.0] |
| Gender (%) | Male | 8804.8 (67.5) | 9051.7 (64.7) |
|  | Female | 4238.2 (32.5) | 4948.3 (35.3) |
| GCS (median [IQR]) |  | 15.0 [15.0, 15.0] | 15.0 [15.0, 15.0] |
| SBP (median [IQR]) |  | 140.0 [125.0, 155.0] | 136.0 [122.0, 150.0] |
| RR (median [IQR]) |  | 18.0 [15.0, 20.0] | 18.0 [16.0, 21.0] |
| 30d survival (%) | Alive | 12437.9 (95.4) | 13470.1 (96.2) |
|  | Dead | 605.1 (4.6) | 529.9 (3.8) |
| ISS (median [IQR]) |  | 4.0 [1.0, 10.0] | 4.0 [1.0, 9.0] |
| NISS (median [IQR]) |  | 5.0 [1.0, 16.0] | 4.0 [1.0, 11.0] |
| ISS>15 (%) | Yes | 2375.4 (18.2) | 1735.2 (12.4) |
|  | No | 10667.6 (81.8) | 12264.8 (87.6) |

|  |  |  |  |
| --- | --- | --- | --- |
| characteristic | level | multi centre | single centre |
| n (%) |  | 27043 (2.2) | 5956 (0.5) |
| Age (median [IQR]) |  | 41.0 [25.0, 59.0] | 42.0 [27.0, 59.0] |
| Gender (%) | Male | 17857.5 (66.0) | 4153.5 (69.7) |
|  | Female | 9185.5 (34.0) | 1802.5 (30.3) |
| GCS (median [IQR]) |  | 15.0 [15.0, 15.0] | 15.0 [14.0, 15.0] |
| SBP (median [IQR]) |  | 139.0 [124.0, 153.0] | 140.0 [124.0, 157.0] |
| RR (median [IQR]) |  | 18.0 [16.0, 21.0] | 18.0 [15.0, 20.0] |
| 30d survival (%) | Alive | 25909.2 (95.8) | 5629.8 (94.5) |
|  | Dead | 1133.8 (4.2) | 326.2 (5.5) |
| ISS (median [IQR]) |  | 4.0 [1.0, 9.0] | 5.0 [1.0, 14.0] |
| NISS (median [IQR]) |  | 4.0 [1.0, 12.0] | 9.0 [3.0, 22.0] |
| ISS>15 (%) | Yes | 4110.4 (15.2) | 1467.6 (24.6) |
|  | No | 22932.6 (84.8) | 4488.4 (75.4) |

GCS, glasgow coma scale; SBP, systolic blood pressure; RR, respiratory rate; ISS, injury severity score; NISS, new injury severity score

## Development and validation

During model development, the number of imputations used for each data set was 44, 48 and 37 for the high and low volume data set, the metropolitan and non-metropolitan data set, and the multi- and single centre data set, respectively.

Table 2 shows model validation performance. The model with the lowest validation mistriage rate was the non metropolitan model with a median mistriage rate of 0.200 (0.190 - 0.380). Performance in terms of undertriage and overtriage rate for the same model was 0.050 (0.040 - 0.070), and 0.160 (0.130 - 0.340) respectively. The worst validation performance (i.e. highest mistriage rate) was found in the single centre sample, with a model median mistriage rate of 0.530 (0.420 - 0.630).

**Table 2. Model validation performance, i.e. performance when applied to the sample in which the model was created.** Data is presented as point estimates with 95% Uncertainty Intervals (95% UI).

|  |  |  |
| --- | --- | --- |
|  | high volume | low volume |
| Mistriage | 0.230 (0.150 - 0.370) | 0.450 (0.370 - 0.610) |
| Undertriage | 0.050 (0.040 - 0.070) | 0.030 (0.020 - 0.040) |
| Overtriage | 0.180 (0.080 - 0.328) | 0.420 (0.340 - 0.580) |

|  |  |  |
| --- | --- | --- |
|  | metropolitan | non metropolitan |
| Mistriage | 0.360 (0.250 - 0.500) | 0.200 (0.190 - 0.380) |
| Undertriage | 0.060 (0.040 - 0.070) | 0.050 (0.040 - 0.070) |
| Overtriage | 0.300 (0.180 - 0.450) | 0.160 (0.130 - 0.340) |

|  |  |  |
| --- | --- | --- |
|  | multi centre | single centre |
| Mistriage | 0.250 (0.150 - 0.320) | 0.530 (0.420 - 0.630) |
| Undertriage | 0.050 (0.040 - 0.060) | 0.050 (0.030 - 0.090) |
| Overtriage | 0.200 (0.100 - 0.280) | 0.480 (0.350 - 0.590) |

## Comparison

Model performance after transfer was determined for each model being transferred to the other sample in the data set, in all data sets (Table 3). When transferred, the model with the lowest mistriage rate was the low volume model with a median mistriage rate of 0.190 (0.130 - 0.840). The model with the highest mistriage rate after transfer was the high volume with a median mistriage rate of 0.550 (0.200 - 0.800).

**Table 3. Model transfer performance, i.e. performance when transferred to the other sample in the same data set.**  Data is presented as point estimates with 95% Uncertainty Intervals (95% UI).

|  |  |  |
| --- | --- | --- |
|  | high volume | low volume |
| Mistriage | 0.550 (0.200 - 0.800) | 0.190 (0.130 - 0.840) |
| Undertriage | 0.030 (0.000 - 0.140) | 0.080 (0.000 - 0.120) |
| Overtriage | 0.510 (0.080 - 0.800) | 0.120 (0.010 - 0.830) |

|  |  |  |
| --- | --- | --- |
|  | metropolitan | non metropolitan |
| Mistriage | 0.510 (0.150 - 0.840) | 0.300 (0.240 - 0.630) |
| Undertriage | 0.020 (0.000 - 0.080) | 0.060 (0.030 - 0.180) |
| Overtriage | 0.480 (0.070 - 0.840) | 0.240 (0.070 - 0.590) |

|  |  |  |
| --- | --- | --- |
|  | multi centre | single centre |
| Mistriage | 0.420 (0.180 - 0.550) | 0.270 (0.160 - 0.798) |
| Undertriage | 0.070 (0.030 - 0.130) | 0.050 (0.010 - 0.120) |
| Overtriage | 0.350 (0.060 - 0.520) | 0.210 (0.070 - 0.790) |

Table 4 shows the transferred model performance when compared to the validation performance in the sample reciving the transferred model. The highest mistriage rate when compared to the reciveing sample validation model performance was found in the metropolitan model, with a median mistriage rate difference of 0.300 (-0.080 - 0.640), meaning this model performed worse when transferred to the other sample in the same data set. In clinical terms, this model transfer means that among 100 trauma patients, 30 more patients would be wrongly classified as major or minor trauma.

**Table 4. Comparison mistriage, i.e. sample validation performance subtracted from transferred performance.** Data is presented as point estimates with 95% Uncertainty Intervals (95% UI).

|  |  |  |
| --- | --- | --- |
|  | high volume | low volume |
| Mistriage | 0.090 (-0.320 - 0.368) | -0.050 (-0.190 - 0.600) |
| Undertriage | 0.010 (-0.030 - 0.110) | 0.020 (-0.050 - 0.070) |
| Overtriage | 0.090 (-0.400 - 0.390) | -0.070 (-0.250 - 0.658) |

|  |  |  |
| --- | --- | --- |
|  | metropolitan | non metropolitan |
| Mistriage | 0.300 (-0.080 - 0.640) | -0.050 (-0.330 - 0.090) |
| Undertriage | -0.030 (-0.050 - 0.040) | 0.010 (-0.030 - 0.130) |
| Overtriage | 0.330 (-0.110 - 0.690) | -0.060 (-0.440 - 0.110) |

|  |  |  |
| --- | --- | --- |
|  | multi centre | single centre |
| Mistriage | -0.120 (-0.230 - 0.220) | 0.020 (-0.140 - 0.528) |
| Undertriage | 0.020 (-0.030 - 0.080) | 0.000 (-0.050 - 0.060) |
| Overtriage | -0.140 (-0.290 - 0.250) | 0.020 (-0.190 - 0.570) |

# Discussion

This study aimed to assess how transfers of clinical prediction models for early trauma care between different contexts within a single health system affect mistriage rates. In all data sets, model transfer between samples resulted in substantial uncertainty in its effect on model performance. When comparing transferred performance to the receiving sample validation performance, the resulting differences also showed considerable uncertainty.

The most notable effects on model performance following model transfer were seen after transferring the metropolitan model. This transfer resulted in an increase of the mistriage rate by 0.300. Mainly contributing to this was a marked increase in overtriage. For this transfer, the 95% UI ranged from -0.080 to 0.640, indicating a high level of uncertainty and that our findings are compatible with a -0.080 decrease to a 0.640 increase in mistriage. The negative 95% UI of -0.080 would signify an improvement in model performance. The higher 95% UI of 0.640 would mean a marked increase in model mistriage, compared to the point estimate of 0.300.

Due to centralized trauma care, non-metropolitan centres generally have fewer resources and less experience receiving trauma patients. They may rely on clinical prediction models more heavily for accurate trauma triage, and an increase in overtriage can lead to further strains on already limited resources. Increased undertriage could possibly lead to increased patient mortality.

Recognizing these risks and updating models accordingly could lead to increased accuracy during trauma patient triage, potentially saving lives by minimizing undertriage, and likely save resources by minimizing overtriage. With registries such as SweTrau, analysis of model transfer could be performed continuously to optimize models currently in use and advise which model transfers might be detrimental (or potentially beneficial).

The transfer of clinical prediction models in trauma care has not previously been studied extensively. In 2016, Gerdin et al. found model transfer to adversely affect model performance in terms of calibration, but that this could be improved by updating the model [9]. This study did not examine model performance in terms of calibration, neither were the effects of updating the model explored.

External validation as the evaluation of a clinical prediction model in a setting in which it was not originally developed has been studied more extensively. Studies using simulated clinical prediction models based on different predictors showed a decline in model performance when being externally validated [21, 24]. A study from 2018 examining the external validity of prediction models for coronary artery disease (CAD) [25], showed models significantly underestimating the probability of CAD. The combined results of this study, the studies on model transfer and the studies on external validation would suggest caution when transferring models.

## Strengths and limitations

### Strengths

The main strength of this study is that its design realistically reflects potential model transfers: clinical prediction models for trauma are usually developed in large metropolitan centres and then transferred as clinical recommendations to minor non-metropolitan centres. The results should therefore be of practical importance.

### Limitations

Originally, all single centres with a valid number of events were to constitute a data set, but only one centre provided a sufficient number of events, leading to the loss of the individual centres data set. This data set could have provided interesting results reflecting realistic situations.

This study used GCS, RR and SBP as predictors for 30-day mortality. Additional predictors such as age, mechanism of injury, or newer predictors like shock index might increase model performance. Furthermore, we used 30-day mortality as outcome, recognizing that late mortality, time in hospital, functional impairment, and morbidity are also important outcome factors in the context of trauma care.

The predetermined analysis plan was to be followed in a step-by-step fashion. Programming challenges and late-time code inclusions required a flexible approach to this analysis plan, sometimes with revisions of previous steps. This is not optimal, and efforts were made to not deviate in any major way. Using GitHub, all code was made public for inspection and to ensure reproducibility [10].

## Conclusion

Model transfer resulted in large and varying levels of uncertainty in its effect on mistriage. Therefore, model transfer can be unpredictable, potentially leading to increased mistriage, but in some cases also to a decrease in mistriage. Noticeably, transfer of the metropolitan model lead to an increased mistriage of 0.300 (-0.080 - 0.640). This observed effect was also associated with considerable uncertainty. Recognizing the limitations of this study, the authors believe further studies are warranted due to the potential economic costs and patient consequences of poor model transfers.

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