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Patient length of stay in trauma networks: Insights from advanced modelling

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ABSTRACT

Length of Stay (LOS) serves as a critical metric for assessing the quality of care within trauma systems, reflecting a healthcare system's efficacy in managing patient flow and resource allocation. However, evaluating the total patient LOS from a comprehensive trauma network perspective remains challenging. This study aims to identify key driving factors influencing LOS in the trauma network, using a dataset containing 26,238 admissions to various institutions within the South Wales Major Trauma Network from January 2012 to August 2021. Given that LOS distributions are typically right-skewed, this paper develops three models to understand their variation, including LASSO Regression, Random Forest, and Generalised Additive Model. Each model incorporates preprocessing strategies to address the right-skewed nature of LOS. Our analysis shows that the LASSO Regression model demonstrates superior performance compared to benchmarks. Significant predictors of LOS are identified, which include the frequency of surgeries (five and six times), patient age (over 75), specific ward types (Burns, Spinal injury unit, Gietaritic, neurosurgical rehabilitation, etc.) and their interactions with ward transfer times and transfer status. These insights are important for clinical stakeholders who manage the trauma systems and make various decisions, including bed allocation, staffing decisions, and discharge rehabilitation planning.

1. Introduction

Length of Stay (LOS) can serve as a proxy for resource allocation, the severity of patient conditions, and crowdedness. Unnecessary delays in LOS can negatively impact the clinical, financial, and operational aspects of health services (Rojas-García et al., 2018). The study of Almaghrabi et al. (2021) identifies in-hospital and intensive care unit (ICU) LOS as key features significantly impacting trauma outcomes. It demonstrates that incorporating these LOS metrics improves the accuracy and reliability of trauma outcome predictions, facilitating more informed clinical decision-making and resource management in trauma care. From a broader healthcare system perspective, the delivery of trauma care is structured through trauma networks, which are organised systems that integrate pre-hospital services, trauma centres, and rehabilitation facilities based on established protocols and pathways to deliver coordinated care for trauma patients. Therefore, understanding the factors that influence LOS throughout such integrated trauma networks is essential for optimising system-wide resource allocation, improving patient outcomes across whole care pathways, and developing evidence-based network policies.

A number of studies have examined the impact of different predictors on the LOS in trauma care, but the findings have been mixed. In general, the combination of patient demographics (age, gender, insurance status) and clinical variables (vital sign measurement, comorbidity) was widely considered for LOS statistical modelling. However, based on the response variables (ICU LOS, extended LOS) and the different types of research data, several surgical (type of surgery or infection) or hospital characteristics (type of admitted trauma facility, direct or indirect transfer) were also identified in the LOS prediction model (Belderrar & Hazzab, 2017; Chona et al., 2017). Moreover, several additional factors, including trauma-related scores (Staziaki et al., 2021) and trauma imaging parameters (Stewart et al., 2021), were also examined as significant predictors for predicting LOS. Although certain studies have examined LOS across a comprehensive trauma network level through descriptive analyses or systematic audits, they typically emphasise variations in LOS across different levels of trauma centres or compare LOS in hospitals within and outside trauma networks (Kuimi et al., 2015; Moore et al., 2014; Morgan et al., 2020). More extensive predictive modelling focuses on individual units, such as emergency departments (ED) or ICU. As a result, there is a restricted comprehension

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of the variables influencing LOS throughout the entire network, particularly as critically injured patients may necessitate multiple transfers and specialised resources that can extend hospitalisations.

Additionally, studies modelling LOS in trauma systems often rely on a single methodological approach, such as regression analysis. In this study, we aim to address these gaps in the literature. Our contributions are summarised as follows:

1. Using a comprehensive dataset from the South Wales Trauma Network (SWTN), including LOS and its 53 potential drivers across the entire trauma network, rather than focussing on single units such as the critical unit or emergency department as the current literature.
2. Developing a LASSO regression model to explain the variation in LOS and comparing its performance against two benchmarks: the generalised additive model (GAM) and random forest (RF).
3. Identifying and interpreting novel factors that contribute to variations in LOS within the trauma network, offering new insights that can inform both clinical practice and healthcare policy.

The remainder of this article is structured as follows. In Section 2, we provide a brief review of the literature and discuss its limitations to position our work. In Section 3, we describe the data set and visualise some key characteristics of the data. In Section 4 we present model development and discuss the evaluation performance. In Section 5, we first present evaluation metrics, followed by discussing the model diagnostic and the main drivers of LOS in the trauma system. In Section 6, we summarise our findings and present ideas for future research.

2. Literature review

To understand the drivers of LOS in trauma, various methodologies have been employed, including ordinary least squares (OLS) linear regression, generalised linear models (GLM), and machine learning (ML) approaches. The distribution of LOS in hospitalisations is widely known to be right-skewed, plurimodal, and inclusive of outliers (Faddy et al., 2009; Ickowicz & Sparks, 2017; Williford et al., 2020) and there has been an ongoing debate regarding the methodologies for modelling such data. Table 1 presents a comprehensive summary of prior studies focused on modelling LOS in trauma cases, alongside a comparison with the general modelling framework employed in this research. The subsequent section will elaborate on the detailed development of the modelling approach.

GLM is one of the most commonly applied families of models for skewed LOS data, as demonstrated by multiple studies (Chona et al., 2017; Kashkooe et al., 2020; Straney et al., 2010; Williford et al., 2020). Straney et al. (2010) used a Gamma mixed-effects regression model to reveal significant variation in paediatric ICU LOS not accounted for by patient case-mix, suggesting inefficiencies in ICU processes. Chona et al. (2017) employed a negative binomial regression model to create a personalised LOS calculator for orthopaedic trauma patients, highlighting the impact of post-operative complications on LOS. Kashkooe et al. (2020) applied Poisson regression to identify factors such as age, gender, infection, and injury severity as significant predictors of prolonged LOS in trauma patients. Williford et al. (2020) used a Gamma mixture regression model to effectively manage the right-skewed distribution of LOS data, enhancing the predictive power for hospital inpatient stays.

Some studies have used OLS-type models, particularly multivariate linear regression with log transformation, to identify key predictors influencing LOS in various patient cohorts. Douleh et al. (2017) investigated the impact of postoperative cardiac complications on LOS in orthopaedic trauma patients, identifying significant predictors of prolonged hospital stays. Zhang et al. (2020) examined factors affecting LOS in patients with traumatic spinal cord injury, highlighting surgery, urinary infections, and poorer functional status as key predictors. Additionally, Moore et al. (2014) analysed trauma patient data across Canada, identifying predictors such as discharge destination, age, and injury severity. These studies focus on understanding and explaining the influence of specific factors on LOS, providing insights into the relationships between variables and demonstrating the utility of OLS-type models in pinpointing critical predictors of LOS. However, Faddy et al. (2009) and Manning and Mullahy (2001) argue that using logarithmic transformations in OLS regression to model LOS is subject to certain limitations. Specifically, Faddy et al. (2009) argues that log-transformed LOS, focusing on geometric means, is challenged by retransformation complexities, particularly due to heteroscedasticity. Moreover, it is suggested that these retransformation issues are effectively addressed, and performance is surpassed in other distributions, like log-normal and Weibull, by a Generalised Linear Model (GLM) with a gamma distribution and a log-link function.

Moreover, several studies have employed machine learning techniques to model LOS. Xu et al. (2022) used a two-stage hybrid classification-regression model to model in-hospital LOS for 42,209 elective surgeries. They compared various models, including linear regression, Random Forests, and multilayer perceptron, finding that predicting longer LOS was particularly challenging and necessitated a combination of classification for long/short LOS and regression for short LOS predictions. Similarly, Gibbs et al. (2021) applied machine learning models, including a nested mixed-effects model and stochastic gradient boosting, to model LOS in paediatric trauma patients. In another study, Belderrar and Hazzab (2017) utilised hierarchical genetic algorithms and fuzzy radial basis function networks to predict the high LOS outliers in critical intensive care units. Additionally, Staziaki et al. (2021) developed artificial neural network (ANN) and support vector machine (SVM) models to model ICU admission and extended LOS after torso trauma. Moreover, He et al. (2021) employed a neural network-based multi-task learning model (ANNML) a model, which has shown promising results in predicting inpatient flow and LOS by simultaneously processing mixed types of prediction tasks. These studies highlight the potential of machine learning models to enhance LOS predictive accuracy and handle complex, nonlinear relationships in healthcare data. However, these models are generally less interpretable than OLS and GLM models.

The literature on LOS modelling in trauma often focuses on individual units such as the ED and ICU, rather than considering the entire trauma system. Therefore, it is essential to shed light on the drivers of LOS within the entire trauma network, as this is fundamental to understanding the overall system rather than just a single unit. Furthermore, although various publications have used regression and machine-learning approaches for length-of-stay prediction in different clinical settings, to our knowledge, few studies have simultaneously compared the three specific model 'families', (i) simple and interpretable linear regression with regularisation (e.g., LASSO), (ii) semi-parametric frameworks (e.g., GAM) to account for nonlinearity, and (iii) tree-based machine learning approaches (e.g., Random Forest) within the same comprehensive trauma network context. Additionally, there is a lack of transparency in the current literature regarding methodology and model design, which is a drawback for reproducibility. To address this, it is important to share data and code to enhance reproducibility. While we do not have permission to share the data, we provide the R code used in our analysis in the supplementary materials.

3. Data

3.1. Data source

This research was carried out within the South Wales Trauma Network (SWTN) in the UK. Access to the Trauma Audit and Research Network (TARN) dataset for patients admissions in South Wales was granted through the Secure Anonymised Information Linkage (SAIL)

Table 1
Comparative research of LOS forecasting models.

Reference	OLS	GLM	ML	Applied model	Dataset	Outcome Type	Study focus	Model evaluation metrics
Belderrar and Hazzab (2017)			✓	The hierarchical genetic algorithm (HGA) and fuzzy radial basis function networks (FRBFN)	26,897 admissions from five different intensive care units	Regression	Predictor identification for LOS	MAE, Mean Magnitude Relative Error (MMRE) and Prediction at level q (Pred(q))
Chona et al. (2017)		✓		Negative binomial regression	49,778 orthopaedic trauma surgery between 2006 and 2013 from the ACS-NSQIP	Regression	Predictor identification for LOS	Beta coefficients and Incidence rate ratios (IRR)
Douleh et al. (2017)	✓			Multiple linear regression without transformations	56,217 orthopaedic trauma patients from 2006 to 2013 in the ACS-NSQIP database	Regression	Predictor identification for LOS	Not specified
Faddy et al. (2009)		✓		Gamma distribution Model, Log-normal Distribution Model, Markov process model with six phases	1,901 patients from 2 hospitals	Regression	Model comparison studies for skewed LOS data	Log-likelihood values, residual quantile–quantile plots, BIC values, generalised Pearson statistics
Gibbs et al. (2021)		✓	✓	Nested mixed effects model; Stochastic gradient boosting model	81,929 paediatric patients from 27 hospitals with a primary diagnosis of trauma	Classification	LOS forecasting study	AUC, ROC, Sensitivity, PPV, NPV, F1 score, and NNE
He et al. (2021)			✓	Artificial neural network-based multi-task learning model (ANNML)	3,500 patients admitted to a hospital in New York City in 2016	Regression	LOS forecasting	loss, MAE, and MSE
Kashkooe et al. (2020)		✓		Poisson regression	14,054 trauma patients	Regression	LOS forecasting study	Not specified
Manning and Mullahy (2001)	✓	✓		OLS for log dependent variables with homoscedastic retransformation, Nonlinear least-squares (NLS) with log link, Poisson regression with log link, Gamma regression with log link	Not applicable (simulation-based analyses)	Regression	Model comparison studies for skewed LOS data	Bias and precision
Moore et al. (2014)	✓			Multilevel linear regression with natural logarithm transformations	126,513 patients discharged alive from Canadian trauma centres between 1999 and 2010	Regression	Predictor identification for LOS	R squares
Straney et al. (2010)		✓		Gamma distributed mixed-effects regression	47,068 admissions from ANZPIC Registry	Regression	Model comparison studies for skewed LOS data	ROC, Lin's concordance correlation coefficient and adjusted pseudo R square
Staziaki et al. (2021)			✓	SVM, Artificial neural networks (ANN)	723 admissions with torso injuries to a Level 1 trauma centre	Classification	LOS forecasting study	AUC
Williford et al. (2020)		✓		Gamma mixture regression models	New York State Hospital inpatient discharges in 2014	Regression	LOS forecasting study	AIC
Xu et al. (2022)	✓		✓	LASSO regression, RF and multilayer perceptron with data truncation	42,209 elective inpatient procedures	Regression	LOS forecasting study	MSE, MAE and MRE
Zhang et al. (2019)		✓		Lognormal–exponential mixture model (LEMM); Lognormal–gamma mixture model (LGMM); Lognormal–lognormal mixture model (LLMM)	Not specified	Regression	Model comparison studies for skewed LOS data	Cramer–Von Mises goodness-of-fit test
Zhang et al. (2020)	✓			Multivariable linear regression model with natural logarithm transformations	631 patients with traumatic spinal cord injury	Regression	Predictor Identification for LOS	Not specified
Current paper	✓	✓	✓	LASSO regression, RF and GAM	26,238 admissions from TARN dataset	Regression	Predictor identification for LOS	RMSE, MAE and R square

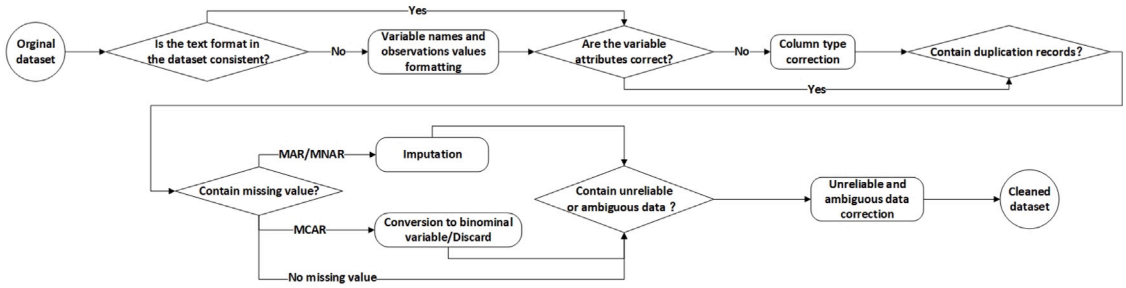


Fig. 1. Work flow of data cleaning.

Table 2
General description of predictors.

Predictor types	Names
Clinical	mtc, casemtc, mechanism, mechanism type, location, arrival mode, EMRTS, wented, tteam, msen, first doctor, nice, intubvent, caseintubvent, pre_intubvent, edintubvent, caseedintubvent, ttop, caseop, ttct, head, face, thorax, abdomen, spine, pelvis, limbs, other, most_severe, outreason, ISS, ps14, outtext, casedied, transfertype, txaloc, knownoutcome, caseknownoutcome, ed_gcs, ed_pulse, ed_resp_rate, ed_sbp, ct_scan, head_operation, head_ct_scan, have_operation, EAU, Orthopaedic, Major_trauma_ward, Medical_ward, Neurosurgical_rehabilitation, Surgical_ward, General_acute, Cardiothoracic, Spinal_injuries_unit, Geriatric, Plastic_surgery, Maxillofacial, CCU, General_paediatric, PACU, Burns, n_ward, rts, triss
Demographical	welsh incident, welsh resident, welsh hospital, countryid, age, gender
Weekday	arrival day of week, discharge day of week

databank. A data-sharing agreement, essential for the entire research project, was established between TARN and SAIL, supported by an approval from the Confidentiality Advisory Group (CAG) committee of the health research authority in the UK. This agreement allows authors to access the dataset and also grants authorisation to publish results obtained from the pertinent dataset. The raw data accessible via SAIL includes 26,238 admissions to various institutions within the SWTN from January 2012 to August 2021. These institutions comprise a Major Trauma Centre, specialised acute hospitals with trauma units, a rural trauma facility, and a local emergency hospital. For each admission, 137 distinct variables are recorded.

3.2. Data quality check and preprocessing

The quality of the raw data acquired was rigorously assessed based on the completeness, plausibility and conformance data quality frame work (Kahn et al., 2016) to ensure its suitability for analysis. The data cleaning process involved several key steps: formatting the data, imputing missing values, and correcting any implausible entries. The whole procedures are illustrated in Fig. 1, which visually represents the data preparation workflow.

Following data preprocessing, we had to remove 10,389 observations. Consequently, after the data quality check, the cleaned dataset contains 15,849 observations and 53 variables. The names and types of all predictors are catalogued in Table 2. For detailed descriptions of each predictor, please refer to Table 6 in Appendix A. Furthermore, please refer to Table 5 in the appendix, which describes several common variables utilised in this paper and documented in previous literature reviews. Before using this data for modelling, we applied feature engineering to create new variables that could enhance the model's performance in explaining the LOS. The feature engineering applied to this dataset is detailed in Section 4.1.

3.3. Response variable

The target variable is the total LOS in the trauma network, which is defined as the duration from a patient's arrival at a specific healthcare facility in the trauma network until their discharge, including a series of clinical events and multiple transfers or admissions in different hospitals (Fig. 3).

The LOS exhibits a rightward skewed distribution (Fig. 4) with a median of 10 (IQR, 5–18) and a mean of 15.26 ± 20.28 days.

3.4. Potential drivers of LOS

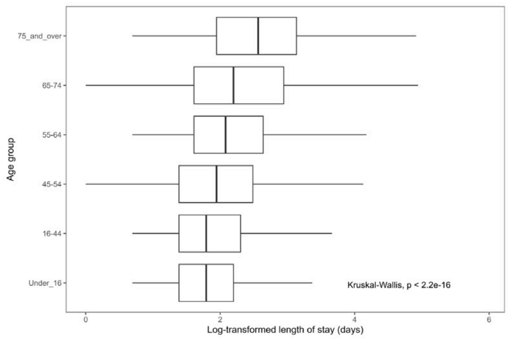
After preprocessing the dataset, our dataset comprises 6 demographic predictors, 65 clinical predictors, and 2 calendar variables. The demographic predictors provide insights into patient origin, detailing attributes such as age, gender, and the classification of postcodes for patients and incident locations within Wales. The clinical predictors encompass a broad range of variables, including physiological measurements (e.g., GCS, respiratory rate, pulse, SBP) and injury-related variables—such as mechanisms of injury and the Abbreviated Injury Scale (AIS) maximum severity for specific body regions, experiences of specific clinical events (operations, CT scans, intubation), and admission details (types of wards and a total number of admissions).Additionally, they encompass details of the initial clinical assessment, such as whether patients were treated by the Emergency Medical Retrieval and Transfer Service (EMRTS), the level of the first doctor, and the most senior doctor to see the patients, along with transfer status and types. The weekday variables document the arrival and discharge day of the week for the patients.

Prior to modelling, an initial visual analysis of all predictors is performed to understand the effect of predictors on LOS using data visualisation. Fig. 2 showcases a subset of these predictors, highlighting those with the potential to influence the LOS. The visualisation could also be useful in identifying the potential interaction effect of predictors to be used in the modelling.

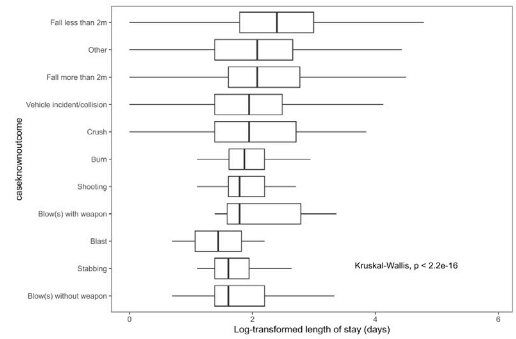
4. Model development

In this study, we adopt three models—LASSO regression, GAM, and RF—that represent the OLS with regularisation, GLM-based, and ML families, respectively. These models were selected to achieve a balance between interpretability and predictive accuracy: LASSO performs automatic feature selection to identify influential predictors, GAM maintains interpretability whilst accommodating non-linear relationships, and Random Forest captures complex interactions with minimal assumptions. Despite the fact that more advanced deep learning models (e.g., Gradient Boosting, Neural Networks) are also employed in LOS forecasting studies, these three models are more in line with our primary objective of identifying key predictors rather than solely forecasting LOS.

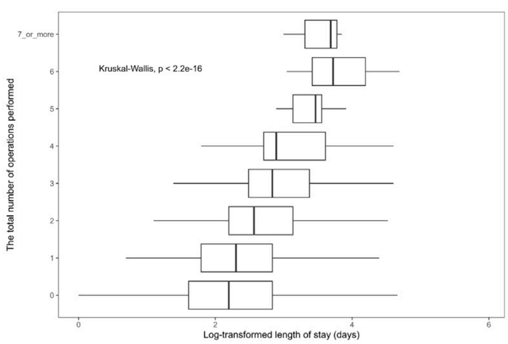
R (version 4.1.2) and RStudio were employed to analyse the dataset, and the'tidymodels' package was utilised for model building and performance assessment, which facilitates a comprehensive and reproducible analysis framework. The general workflow of model development is shown in Fig. 5



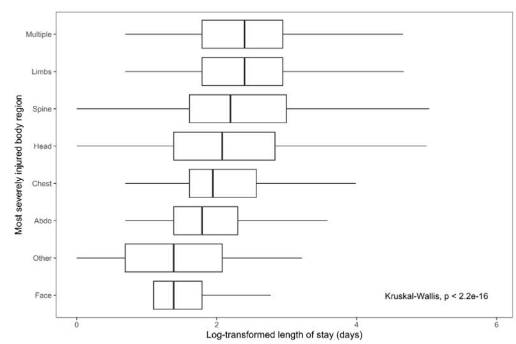
(a) Distribution of LOS across the age group



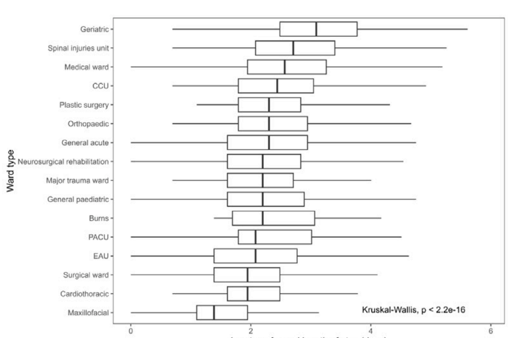
(b) Distribution of LOS across the injury mechanism



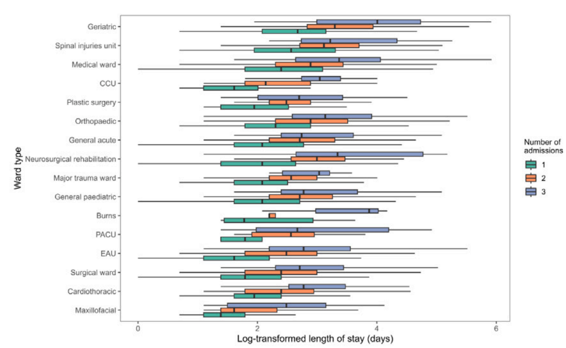
(c) Distribution of LOS across the total number of operations performed



(d) Distribution of LOS across the most severely injured body region



(e) Distribution of LOS across ward types



(f) Distribution of LOS across ward types and its interactions with number of ward admissions

Fig. 2. Initial visualisation of LOS based on identified significant predictors.

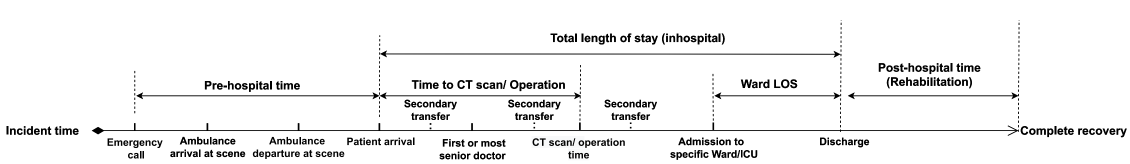


Fig. 3. Trauma pathway illustration.

4.1. Feature engineering

To enhance the performance of our model, established trauma scoring systems were employed as key components of our feature engineering strategy. Notably, the Trauma Injury Severity Score (TRISS) and the Revised Trauma Score (RTS) were integrated, as advocated by recent literature (Stewart et al., 2021). Following the calculation of these scores, intermediate variables were removed to simplify the structure of the dataset, thus facilitating more efficient data processing and analysis.

Furthermore, our exploratory data visualisation analysis (Figs. 2(e) and 2(f)) and clinical consultation revealed that patients requiring multiple ward admissions often accumulate a higher burden of care when

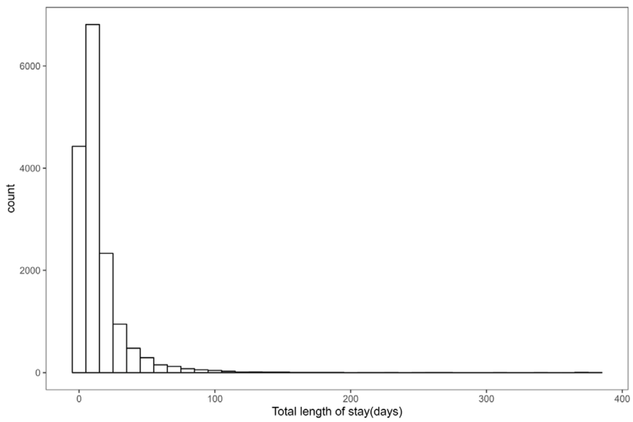


Fig. 4. Histogram of the LOS.

admitted to certain specialised wards (e.g., Burns, Spinal Injuries, Geriatric). These grouped summary statistics showed distinctively longer LOS in these specific patient subgroups, suggesting an interaction effect between the type of ward and the number of admissions. To explicitly capture this effect, we consolidated the original per-admission ward records (Ward1, Ward2, Ward3) into two new sets of variables. First, we created dummy variables for each specialised ward type (Burns, Geriatric, Spinal, etc.) to indicate whether a patient had ever been admitted there across any of their recorded admissions. Second, we defined a categorical variable for the total number of ward admissions (0, 1, 2, or 3+). We then combined these two sets of variables (ward-type dummies and number of ward admissions) to create interaction terms (e.g. a patient with three or more admissions and has once stayed in the Burns ward). This step notes that the combined effect on LOS may exceed the sum of individual risk factors alone, especially in cases where repeated admissions and specialised ward requirements signal more complex care pathways

Additionally, the influence of the ‘weekend effect’ on the LOS was investigated by transforming the date of patient arrival into the corresponding weekday. This conversion yielded a new categorical variable, enabling the exploration of temporal variations in patient flow and their impacts on LOS.

Finally, outliers in LOS were managed through a structured approach to retain clinically meaningful extremes while mitigating their statistical influence. Extreme LOS cases (LOS > 37.5 days), defined as values exceeding $1.5 \times \text{IQR}$ above the third quartile, were flagged using a dummy variable (outlier_flag). This threshold aligned with standard boxplot rules and was validated through prior visualisation analysis of the same dataset (Wang et al., 2024), which revealed distinct patterns between typical LOS (≤ 37 days) and prolonged stays. Prolonged LOS may reflect severe comorbidities, complex care pathways, or administrative delays. The third quantile (Q3) and IQR were computed exclusively from the training set to prevent data leakage. The resulting dummy variable ‘outlier_flag’ was incorporated into all models, enabling explicit differentiation between normal and extreme cases.

After feature engineering, the final dataset used for modelling includes 74 columns (including LOS, and 73 other variables that could be used to describe the variation in LOS) and 15,849 observations, offering a comprehensive foundation for robust statistical analysis and modelling.

4.2. LASSO regression model

LASSO regression represents an extension of Ordinary Least Squares Linear Regression (OLSLR), characterised by its implementation of shrinkage. This method is distinguished by the imposition of a constraint or penalty on the sum of the absolute values of the regression coefficients. Recent studies have shown that it has been effectively applied in hospital settings to predict patients’ times for in-hospital stays. For example, Benevento et al. (2023) study applies LASSO regression to predict waiting times in emergency departments, comparing its effectiveness with other machine learning models. Zhang et al. (2023) applied LASSO regression to develop a predictive model for the hospital LOS of patients infected with the SARS-CoV-2 Omicron variant, identifying key variables that influence it.

LASSO regression is particularly useful for providing feature selection automatically in datasets with a large number of features. Following the description of each predictor, the LASSO regression model is given by:

$$
\begin{aligned}
Y_t = \beta_0 &+ \underbrace{\sum_{j=1}^{65} \beta_j^C X_{t,j}^C}_{\text{Clinical predictors}} + \underbrace{\sum_{j=1}^{2} \beta_{65+j}^W X_{t,j}^W}_{\text{Weekday effect}} \\
&+ \underbrace{\sum_{j=1}^{6} \beta_{67+j}^D X_{t,j}^D}_{\text{Demographic predictors}} + \underbrace{\sum_{j=1}^{30} \beta_{73+j}^I X_{t,j}^I}_{\text{Interaction terms}} + \epsilon_t
\end{aligned}
\tag{1}
$$

The objective function of LASSO regression can be expressed as the minimisation problem of the following form:

$$
\begin{aligned}
\hat{\beta}^{\text{LASSO}} = \underset{\beta}{\operatorname{argmin}} \Bigg\{ \sum_{t=1}^{N} \Bigg(Y_t - \Bigg(\beta_0 + \sum_{j=1}^{66} \beta_j^C X_{t,j}^C \\
+ \sum_{j=1}^{2} \beta_{66+j}^W X_{t,j}^W + \sum_{j=1}^{6} \beta_{68+j}^D X_{t,j}^D + \sum_{j=1}^{30} \beta_{74+j}^I X_{t,j}^I \Bigg) \Bigg)^2 \\
+ \lambda \Bigg(\sum_{j=1}^{65} |\beta_j^C| + \sum_{j=1}^{2} |\beta_{65+j}^W| \\
+ \sum_{j=1}^{6} |\beta_{67+j}^D| + \sum_{j=1}^{30} |\beta_{73+j}^I| \Bigg) \Bigg\}
\end{aligned}
\tag{2}
$$

Where $\hat{\beta}^{LASSO}$ denotes the estimated coefficients obtained by the LASSO, $X_{t,k}$ represents the predictor matrix, Y_t are the observed outcomes, j,k,l,m is the number of predictors, N is the number of observations, and λ is the tuning parameter that controls the strength of the penalty applied to the size of the coefficients. The penalty term $\sum_{j,k,l,m} |\beta_{jklm}|$ imposes a constraint on the sum of the absolute values of the coefficients, effectively conducting variable selection by shrinking some coefficients to exactly zero. In this study,p = 73, $N = 15849$.

Initially, the dataset was split into training (80%) and testing (20%) sets. Preprocessing involved log-transforming the response variable LOS, normalising numeric predictors, converting categorical variables into factors and dummy variables and consolidating rare factor levels. Besides that, interaction terms based on the different ward types and admission times were created. The final preprocessed dataset for LASSO modelling comprises 204 predictors, which include 194 categorical predictors and 10 numeric predictors.

To tune the penalty parameter (λ), a grid search over a logarithmic scale from [0.0001,10] with 100 levels was conducted. A 10-fold cross-validation assessed model performance, with the optimal λ selected based on the lowest Root Mean Square Error (RMSE). After tuning, the λ value yielding the lowest RMSE was utilised to finalise and train the model on the entire training dataset, ensuring optimal predictive performance and reproducibility. The best-performing LASSO models were summarised in Table 3. Please refer to Fig. 8(a) in the appendix for further information on LASSO hyperparameter tunning. As shown, the RMSE reaches its minimum at a moderate level of regularisation, $\lambda \leq 0.001$, signifying an optimal balance between bias and variance. Beyond this threshold, as the regularisation strength intensifies, the RMSE rises precipitously, indicative of excessive penalisation. This over-penalisation leads to a model that compromises predictive accuracy due to its oversimplified complexity.

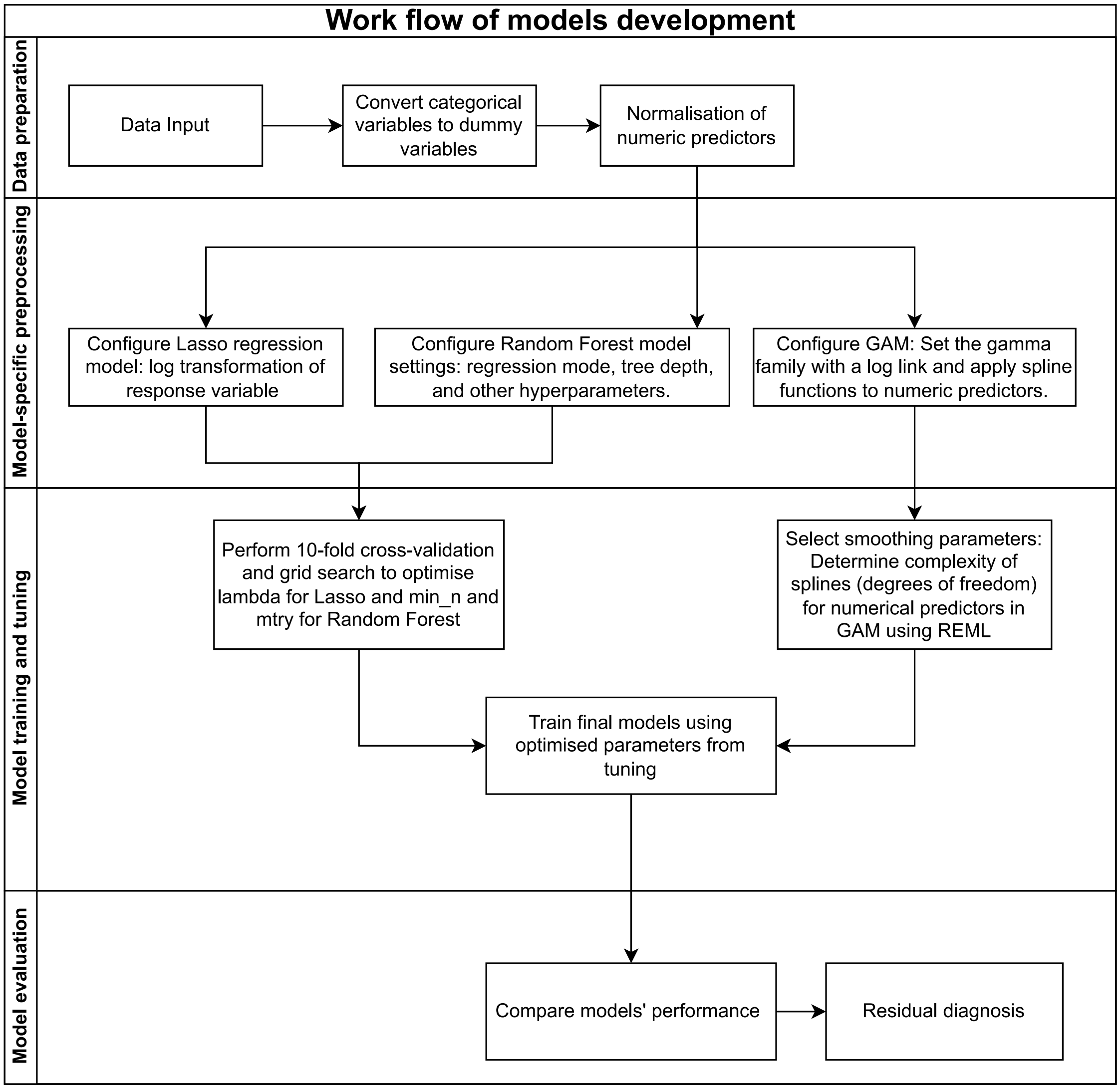


Fig. 5. Work flow of models development.

Table 3
Overview of model setup and configuration.

Model	Data manipulation for Input	Outcome	Parameter tuning	Metrics for tuning parameters
LASSO regression	Normalised numeric predictors, Interaction effects, dummy variable creation based on all categorical variables,	Natural Log transformed LOS	$\lambda = 0.0016$	RMSE
Random Forest	Normalised numeric predictors, Interaction effects, dummy variables creation based on all categorical variables	LOS	mtry = 24, min_n = 5	RMSE
GAM	Normalised numeric predictors, Interaction effects, dummy variables creation based on all categorical variables	LOS (log link used with Gamma family)	Smoothing parameters optimised	Deviance explained

4.3. Random forest

The RF algorithm, developed by Breiman (2001), effectively combines multiple decision trees to enhance prediction accuracy for classification and regression tasks (Biau & Scornet, 2016). This method bootstrapping to train trees on diverse data subsets and aggregates their predictions, achieving robust performance across high-dimensional settings (Benevento et al., 2023; Genuer et al., 2010; Triana et al., 2021). Furthermore, RF provides more interpretable measures of variable importance and fewer tuning parameters than other advanced machine-learning techniques. This is consistent with our main objective of identifying the primary determinants of LOS. This balance of interpretability and predictive accuracy makes RF an appropriate choice for the analysis of heterogeneous data across a multi-institutional trauma network.

Based on the frameworks described by Geetha et al. (2019) and Benevento et al. (2023), the general RF regression algorithm is summarised in Algorithm 1

Algorithm 1 Random Forest Regression Algorithm

Require: N (Number of bootstrap samples), M (Total number of attributes), m (Sample size, number of attributes considered at each split), s (Minimum node size), B (Number of trees)
Ensure: Random Forest model RF

```
for b = 1 to B do
    Draw a bootstrap sample Z*_b of size N from the training data.
    Initialize tree T_b.
    while there are nodes that can be split and node size ≥ s do
        for each node do
            Select m attributes at random from the M attributes.
            Identify the best-split point using the selected m attributes.
            Split the node into two daughter nodes based on the best split.
        end for
    end while
    Add tree T_b to the forest.
end for
To predict at a new data point x, compute:
```

$$f(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

where $T_b(x)$ is the prediction of the b-th tree. **return** RF (ensemble of trees $\{T_b\}_{b=1}^{B}$)

In our implementation, the preprocessed dataset used for RF modelling retains the same configuration as that employed in the LASSO model, except for transforming the LOS. The final preprocessed dataset consistently comprises 194 categorical predictors and 10 numeric predictors. As for the tuning parameters, the total number of attributes (M) was set to 73. Considering computational efficiency (Probst et al., 2019), the number of trees (T) was set to 500. A grid search, combined with 10-fold cross-validation as suggested by Ramadhan et al. (2017), was applied to identify the optimal combination of m (the number of attributes considered at each split) and s (the minimum node size) based on minimised Root Mean Square Error (RMSE). Specifically, to balance the trade-off between tree diversity and predictive accuracy (Probst et al., 2019), the selection range for m was set from 2 to approximately one-third of M (25 out of 73), at 20 different levels. Similarly, in alignment with the tuning strategy proposed by Probst et al. (2019), which suggests that a higher node size (s) reduces computational time without substantially affecting predictive accuracy in large datasets, s was set from 5 to 50, at 20 different levels. Fig. 8(b) visualises the RMSE across varying levels of m and s. The analysis depicted a steep decline in RMSE from $m = 2$ to $s = 5$, beyond which improvements plateaued. This trend persisted across multiple node sizes, indicating a diminishing return on increasing m beyond the optimal point. The combination $m = 24$ and $s = 5$ emerged as the most optimal, aligning with the lowest observed RMSE, thereby informing the retraining of the model with these settings. The performances of the optimised RF model are detailed in Table 5.

4.4. Generalised additive model

The GAM, from the family of GLM, incorporate non-linear associations between covariates and the response variable through smooth functions, enhancing model flexibility and adaptability to complex datasets (Baayen & Linke, 2020). Originally introduced by Hastie and Tibshirani (1986), GAMs allow for the use of various types of smoothers like splines or kernels to model non-linear relationships without assuming any specific parametric form of the covariates. This adaptability makes GAMs particularly effective in fields such as clinical research and mortality modelling, where traditional linear models fail to capture the underlying complexities of data relationships (Austin, 2007; Barrio et al., 2013).

The general form of a GAM can be formally written as:

$$g(\mathbb{E}(Y_i)) = \beta_0 + \sum_{j=1}^{p} f_j(x_{ij}) + \epsilon_i, \tag{3}$$

where g is a link function (which can be identical, logarithmic, or inverse), Y_i follows some exponential family distribution, β_0 is the intercept, f_j are unknown smooth functions of the covariates x_{ij}, and ϵ_i is an i.i.d. random error.

The smooth function f is composed of a sum of basis functions b and their corresponding regression coefficients β, formally written as:

$$f(x) = \sum_{i=1}^{q} b_i(x)\beta_i, \tag{4}$$

where q is the basis dimension. Smooth functions are also called splines, which are real functions defined by polynomial functions (basis functions). The places where the polynomial pieces connect are called knots. In GAMs, penalised regression splines are used to regularise the smoothness of a spline.

Therefore, the model can be written in a linear way as:

$$g(\mathbb{E}(y)) = \mathbf{X}\beta + \epsilon, \tag{5}$$

where $\mathbf{X}$ is a model matrix and β is a vector of regression coefficients. The objective function to be minimised is:

$$\|y - \mathbf{X}\beta\|^2 + \lambda \int_0^1 [f''(x)]^2 dx, \tag{6}$$

where λ is a smoothing parameter and the integral of squares of second derivatives can be written as:

$$\int_0^1 [f''(x)]^2 dx = \beta^{\top}\mathbf{S}\beta, \tag{7}$$

where $\mathbf{S}$ is a matrix of known coefficients. This implies that regression coefficients can be obtained by the equation:

$$\hat{\beta} = (\mathbf{X}^{\top}\mathbf{X} + \lambda\mathbf{S})^{-1}\mathbf{X}^{\top}y, \tag{8}$$

In this study, the GAM employs the same procedure for creating dummy variables as previously described. Following dataset preprocessing, it is structured into three distinct parts. The non-parametric component employs smooth functions, specifically cubic splines, to model all numerical predictors, which include age, time to operation, total numbers of operations, time to CT scan, ISS, probability of survival, RTS, and TRISS. These predictors are chosen based on their significance and continuity, allowing for more flexible modelling of their effects on the LOS. The parametric component incorporates all 162 categorical predictors after dummy variables creation, maintaining a clear distinction in how categorical and continuous data are handled within the model. The third component includes the same 32 interaction terms used by both LASSO and Random Forest, ensuring that the most influential interactions are captured. A gamma family distribution is applied to the model to accommodate the skewed nature of the LOS, which typically involves right-skewed data. This choice enhances the robustness and accuracy of the estimates.

Table 4
Comparison of model performance.

Model	R^2	RMSE	MAE
LASSO	0.5777	0.6160	0.4963
RF	0.5434	12.8064	6.5767
GAM	0.5085	14.0929	7.0447

Following this structured approach, the GAM model is represented as:

$$\eta = \beta_0 + \underbrace{\sum_{i=1}^{162} \beta_i x_i}_{\text{parametric part}} + \underbrace{\sum_{j=1}^{10} s_j(z_j)}_{\text{non-parametric part with cubic splines}} + \underbrace{\sum_{k=1}^{32} \gamma_k w_k}_{\text{interaction terms}} \tag{9}$$

where η represents the linear predictor, β_i are the coefficients for the parametric part, s_j are the smooth functions with cubic splines for the non-parametric part, and γ_k are the coefficients for the interaction terms.

5. Results and discussion

5.1. Model performance

In this study, LOS is analysed as a continuous variable. The performance of different models is quantitatively assessed using five principal metrics employed in regression analysis: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) (Tatachar, 2021).

It is pertinent to note that the 'tidymodels' package in R, which is employed for model fitting, uses a holdout set to measure performance, thus providing a valid estimate of R^2 without the need for adjustment. Adjusted R^2, which typically adjusts for the number of predictors in the model, is not utilised here since the evaluation uses an independent dataset, negating the necessity to account for model complexity through degrees of freedom. This approach ensures that the reported R^2 is both unbiased and indicative of the model's predictive power on unseen data.

The comparative analysis of LASSO, RF, and GAM demonstrated significant disparities in their ability to explain variations in LOS (Table 4). LASSO achieved the highest R^2 (0.5777), demonstrating a better explanatory power for overall variance and relative performance against the naive baseline. Random Forest achieved a slightly lower R^2 (0.5434), while GAM yielded the lowest R^2 (0.5085). Due to the log transformation applied to LOS in LASSO, its RMSE (0.62) and MAE (0.50) are not directly comparable to untransformed models. Between RF and GAM, RF exhibited smaller absolute errors (RMSE: 12.81 vs. 14.09; MAE: 6.58 vs. 7.04).

LASSO model efficiently penalises and excludes less contributory predictors, enhancing both the interpretability and efficiency of the process. The robust performance of the Lasso Regression could also be attributed to the nature of our dataset. The predominance of categorical predictors in the dataset plays to the strengths of Lasso Regression, which reduces overfitting by penalising less informative predictors.

Although RF achieved a relatively good explanatory power R^2 among the three models, its residual variance suggest limitations in predicting extreme or atypical LOS cases. This discrepancy may be attributed to RF's sensitivity to datasets dominated by high-cardinality categorical features, where sparse or rarely observed variable levels can bias splitting decisions during tree construction. Prior research indicates that, under such high-cardinality conditions, tree-based methods may become biased in how they select splits (Boulesteix et al., 2012). Moreover, without appropriate encoding or reduction of categorical information, Random Forest often struggles to parse these settings effectively (Johnson & Khoshgoftaar, 2022). Even advanced ensembles such as boosted decision trees may be adversely impacted by the high cardinality of sparse predictors, compromising both predictive accuracy and the reliability of variable importance measures (Hancock & Khoshgoftaar, 2021). Despite hyperparameter tuning, RF's residual errors remained heteroscedastic, reflecting its difficulty in generalising to subgroups with prolonged LOS—a challenge exacerbated by the dataset's sparsity and skewed distribution.

Our analysis revealed that LASSO eliminated coefficients for 14 predictors, systematically suppressing noise from sparse or weakly associated variables. This feature selection enhanced interpretability and reduced overfitting risks, aligning with its design philosophy of parsimony in high-dimensional settings.

GAM underperformed both RF and LASSO. Although it is well-suited to capturing smooth, nonlinear effects in numeric variables, it could be less efficient in scenarios where most predictors are discrete. In our dataset, more than 90% of the variables were categorical with multiple levels. This large number of factors can lower the effectiveness of smooth functions, introduce sparse categories, and increase the risk of bias in estimated smooth terms.

The following section provides a comprehensive analysis of residual diagnostics, clarifying these trade-offs.

5.2. Model diagnosis

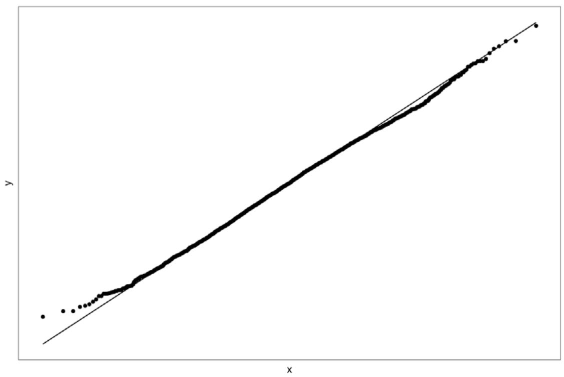
In light of the model performance comparison, we conduct residual diagnostics for LASSO, RF, and GAM to evaluate model fit and robustness, with particular attention to outlier handling.

According to the residual diagnosis of the LASSO regression model, The QQ plot (Fig. 6(a)) shows close alignment with the diagonal for most residuals, suggesting reasonable adherence to normality assumptions in typical cases. Minor deviations in both tails, especially a concentration of upper-tail outliers, could indicate difficulties in predicting extreme LOS values, likely attributable to LASSO's squared-error loss function emphasising central tendency rather than outlier resilience. The residual histogram (Fig. 6(b)) supports this interpretation: while near-symmetrical and centred on zero, its mild right skew reflects occasional overprediction of prolonged LOS cases. This pattern underscores LASSO's suitability for inferential tasks, where interpretability and stability for typical observations outweigh absolute precision at extremes.

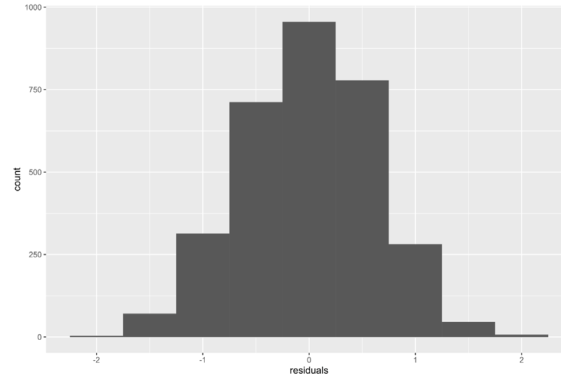
Meanwhile, the RF residual diagnosis demonstrates a different pattern. As shown in Fig. 6(a), the QQ plot indicates that RF residuals deviate significantly from the diagonal, suggesting heavier tails and outliers at both extremes. Although the histogram of residuals (Fig. 6(d)) is centred near zero, it exhibits a pronounced right tail, indicating occasional large positive errors. These findings reflect the model performance results: while RF can capture complex patterns and attain strong explanatory power (i.e., high R square), it also shows higher variance in its predictions, particularly for extreme LOS values.

Similarly, the GAM residual analysis demonstrates substantial departures from normality in both tails of the QQ plot (Fig. 6(e)), suggesting it tends to under or over-predict the most extreme cases. The residual histogram (Fig. 6(f)) further displays a skew towards positive residuals, implying the model systematically overestimates LOS in certain instances. This result aligns with GAM's comparatively lower performance in explaining variance.

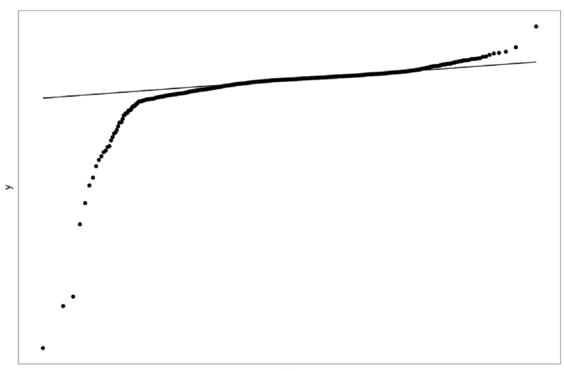
In summary, the LASSO regression model demonstrates the most stable residual behaviour, exhibiting fewer outliers and reduced skewness compared to RF and GAM. This stability is especially beneficial for clinical applications where easily interpretable predictions are essential. Thus, the LASSO model is identified as our recommended method for modelling LOS based on the current research dataset. Although RF and GAM can identify complex, nonlinear patterns, they may require extra optimisation strategies to achieve greater consistency and accuracy, mainly when predicting extreme LOS values.



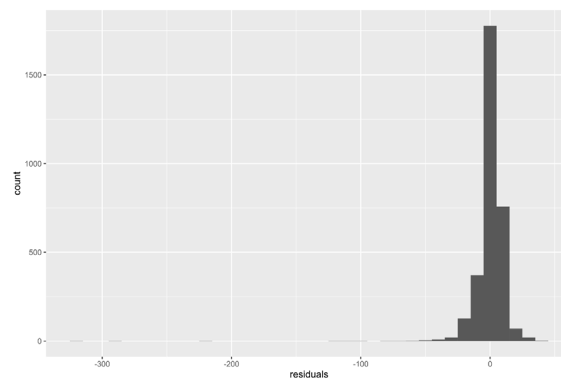
(a) QQ plot of LASSO regression model



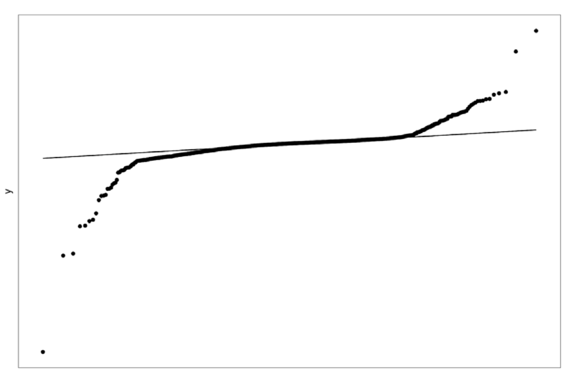
(b) Histogram of residuals of LASSO model



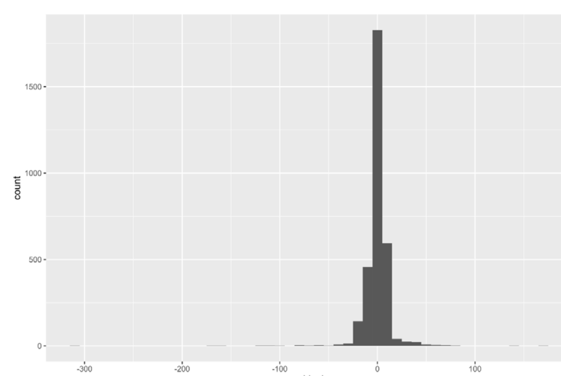
(c) QQ plot of random forest model



(d) Histogram of residuals of random forest model



(e) QQ plot of GAM model



(f) Histogram of residuals of GAM model

Fig. 6. Residual diagnostics of LASSO regression, RF, and GAM.

5.3. Variable importance

Given the superior performance compared to two other models, we examine variable importance of LASSO model for further interpretation of LOS. Out of 204 variables in the preprocessed dataset, the model selected 197 for analysis. Notably, the LASSO regression model excluded multiple subgroups of feature from the final analysis. Specifically, these discarded categories included patients from Wales, incidents occurring on roads or at others' homes, patients who were intubated or ventilated for the entirety of their hospital stay, those who underwent exactly one operation, and an interaction term capturing patients who experienced more than three ward admissions and were admitted to a general acute ward.

In terms of interpreting the LOS, This study identified some important variables that contribute to the LOS. Several variables previously identified as potential determinants of LOS in the data visualisation were further validated through feature selection for the LASSO model.

The feature selection process highlights the model's sensitivity to specific variables that significantly impact LOS. Fig. 7 illustrates the top 30 predictors in terms of relative importance as selected by the LASSO regression model. The colour coding differentiates the direction of the relationship between each predictor and the outcome, where teal bars indicate a positive association (POS) and red bars denote a negative association (NEG) with the target variable. These predictors are ranked from the most to the least influential based on the absolute values of their importance scores.

It can be seen that certain predictors have a substantial influence on the model's estimation of LOS. In particular, the outlier flag demonstrates the most significant positive impact among all variables, highlighting that extremely long stays represent a distinct subgroup with unique determinants. This underscores the importance of identifying

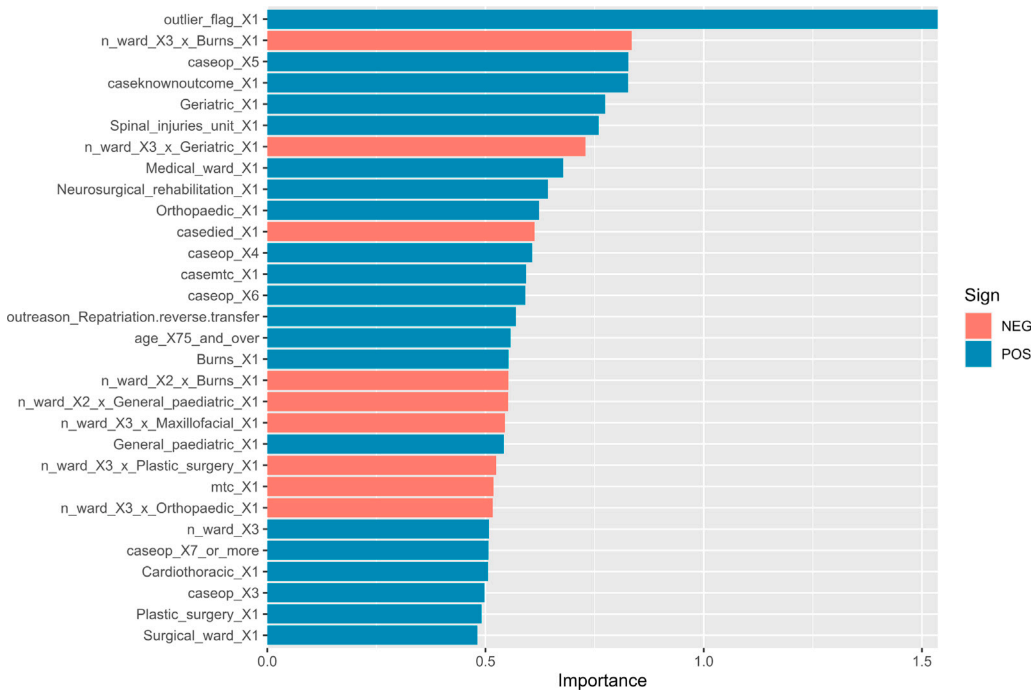


Fig. 7. Variable importance graph based on LASSO regression model: horizontal bars represent selected predictors, with the length corresponding to the magnitude of each variable's importance.

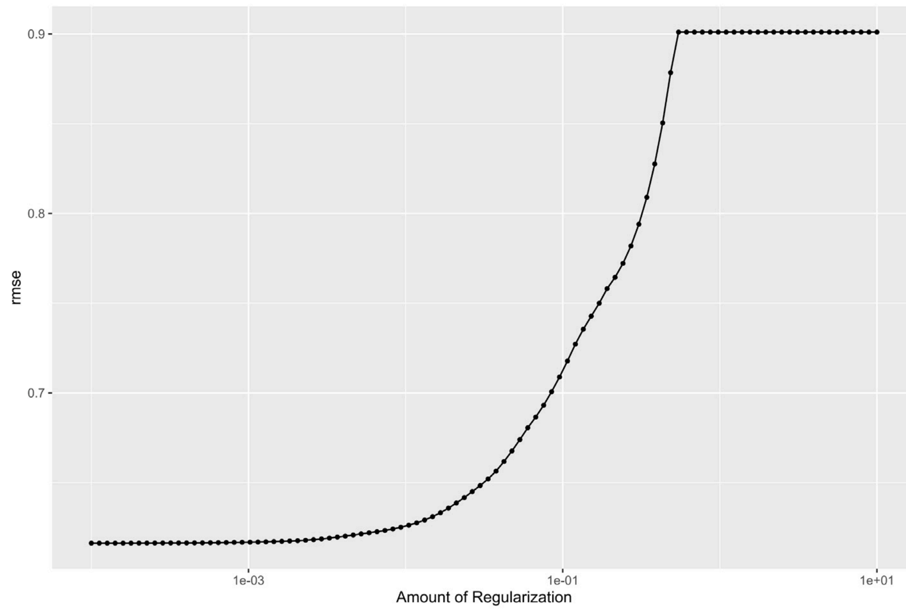
outlier cases to prevent diluting general trends and better manage the distinct clinical and logistical complexities associated with prolonged hospital stays.

Furthermore, admissions to specific ward types have been identified as significant explanatory variables for LOS, with wards such as geriatric, spinal injury unit, medical wards, neurosurgical rehabilitation, orthopaedic ward, burns ward, general paediatric ward, cardiothoracic ward, plastic surgery ward and surgical wards showing pronounced importance in descending order of their scores. Specifically, as discussed by Tal (2021), elderly patients in geriatric wards often experience longer hospital stays due to complex health conditions, including congestive heart failure, hypoalbuminemia, urinary tract infections, pneumonia, and malignancies. The need for polypharmacy, non-independent functional status, frailty, and tube feeding also lead to extended hospital stays. Additionally, the research outlined by Hussain and Dunn (2013) underscores the multifaceted nature of burn care and identifies key predictors influencing the LOS for patients with burn injuries. Full-thickness burns and inhalation injuries notably increase LOS due to the intensive monitoring required and the treatment of complications such as respiratory issues, infections, and cardiovascular problems. Surgical interventions, including escharotomies and skin grafting, address immediate health concerns but also necessitate prolonged recovery and monitoring, further contributing to extended intensive care and comprehensive rehabilitation for severe burns (Hussain & Dunn, 2013). This comprehensive management of complex cases highlights why these factors are critical in predicting extended hospital stays. Collectively, the complex and diverse care required in these specialised wards effectively explains the significant influence of ward type on LOS.

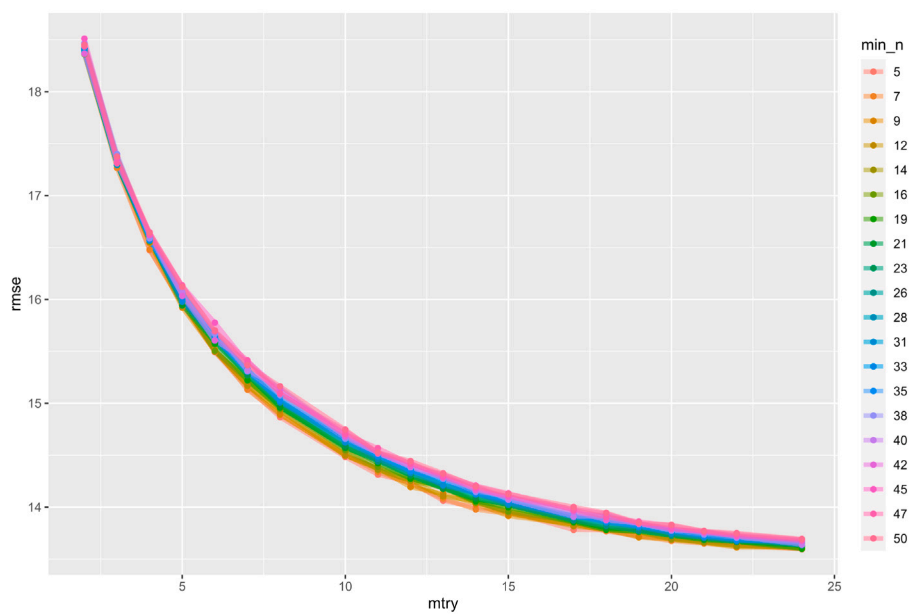
Fig. 3 also highlights key interaction effects between ward type and number of admissions, offering additional insight into how different combinations influence LOS. For example, patients who have been hospitalised twice and admitted to burns or general paediatric wards negatively impact LOS, suggesting that multiple admissions in these particular wards may be associated with more streamlined or less resource-intensive stays. Similarly, patients experiencing three or more admissions in the burns, orthopaedic, plastic surgery, or maxillofacial wards exhibit shorter predicted LOS than one might expect from the primary effects alone. These patterns underscore that the interaction of repeated admissions and specific ward settings can substantially shift LOS outcomes, either by expediting specific procedures and discharges or through more efficient, protocol-driven care.

As for the demographic factors, age notably impacts LOS. Specifically, patients older than 75 years are consistently identified as key predictors of longer LOS. This association underscores the significant influence of advanced age on hospitalisation duration, as corroborated by several studies (Brotemarkle et al., 2015; Chona et al., 2017; Moore et al., 2014; Tal, 2021). These findings across diverse healthcare settings highlight age as a robust predictor of LOS, suggesting that the complexities and heightened care requirements associated with older populations contribute to their extended stays in hospitals. Further research indicates that elderly patients often have slower recovery rates and are more susceptible to hospital-associated complications such as falls, infections, and medication side effects, which can all extend hospital stays. Additionally, the need for comprehensive discharge planning and coordination with long-term care facilities or home care services further complicates and lengthens the discharge process for older adults.

In terms of injury-related predictors, although not among the top 30 predictors in the updated ranking, severe spinal injuries with a maximum Abbreviated Injury Scale (MAIS) severity score of 4 or 5—consistently show a strong positive impact on LOS, as evidenced by importance scores of 0.3034 and 0.3182 respectively. Specifically, MAIS scores greater than 4 indicate severe injuries that require extensive medical interventions, including complex surgical procedures and comprehensive post-operative care, all of which contribute to prolonged hospitalisation periods. This observation aligns with findings from Moore et al. (2014), who identified a clear association between higher MAIS and increased LOS; specifically, patients with an MAIS of 5 or 6 had an average increase in LOS of 4.9 days compared to those with a MAIS of 1 or 2. Furthermore, the significant impact of spinal injuries on LOS is underscored by Mahmoud et al. (2017), who reported that the average LOS for patients with traumatic spinal cord injuries in rehabilitation settings was 84 ± 60 days, with a median of 70 days



(a) Association between the amount of regularisation (lambda) of LASSO and the model's RMSE



(b) RMSE Trends Across Different mtry and min_n Settings in Random Forest Parameter Tuning

Fig. 8. Tuning parameter process for LASSO regression and RF.

and a range from 4 to 419 days. These findings collectively highlight the substantial effect of severe spinal injuries on LOS, emphasising the complex care needs associated with higher MAIS scores.

Additionally, transfer status significantly impacts variations in LOS, as illustrated in Fig. 3. Specifically, the reason for transfer out is repatriation and reverse transfers are associated with longer LOS, while scenarios without transfers generally result in shorter LOS. This finding aligns with the observations of Moore et al. (2014), who noted that in a Canadian trauma registry, patients who were transferred had an average of 2.7 fewer days of hospital stay compared to those who were directly transported. The need for transfers often indicates requirements for specialised medical treatment, higher levels of care, repatriation or capacity constraints, as highlighted in Spering et al. (2023), which inherently prolong LOS. Conversely, patients treated within a single facility without the need for transfer usually experience more direct and efficient care pathways, contributing to reduced hospitalisation durations. Moreover, patients admitted to MTCs throughout their hospital journey typically encounter longer LOS, which reflects the severity of their injuries. MTCs are designed to provide specialised care for patients with severe injuries, often defined as an injury severity score (ISS) greater than 15 (Davenport et al., 2010). As geographic and logistic conditions allow, patients requiring MTC care, including those necessitating secondary transfers, are directed to these facilities (Wohlgemut et al., 2018). Thus, treatment at MTCs, due to the association with severe injuries and potentially complex transfers, also leads to extended durations of hospital stay.

Furthermore, our analysis indicates that the variable 'caseKnownOutcome' (Is the outcome known from all hospital stays?) is significantly associated with the LOS in the trauma network. This association is evident in the boxplot and further supported by LASSO regression

Table 5
Predictors both appeared in LR and TARN data set.

Common predictors	Reference	Similar terms used in LR
Age	Douleh et al. (2017), Gibbs et al. (2021), Brotemarkle et al. (2015), Belderrar and Hazzab (2017), Zhang et al. (2020), Moore et al. (2014), Staziaki et al. (2021), Morshed et al. (2015), Chona et al. (2017)	Age
Gender	Douleh et al. (2017), Gibbs et al. (2021), Brotemarkle et al. (2015), Belderrar and Hazzab (2017), Zhang et al. (2020), Moore et al. (2014), Staziaki et al. (2021), Morshed et al. (2015), Chona et al. (2017)	Sex
Head, face, thorax, limb, abdomen, Spine, pelvis, most severe	Gibbs et al. (2021), Chona et al. (2017), Zhang et al. (2020), Moore et al. (2014)	Anatomic region of injury, Trauma/injuries and related conditions, Level of injury, Body region of the most severe injury
CT scan (0,1)	Belderrar and Hazzab (2017)	has Chart event
CaseOP Op (has or not have Operation)	Belderrar and Hazzab (2017), Stewart et al. (2021), Moore et al. (2014)	has Lab event, has Surgery (OR)
mech	Zhang et al. (2020), Staziaki et al. (2021), Moore et al. (2014)	Cause of injury, Trauma mechanism, mechanism
ISS	Stewart et al. (2021), Belderrar and Hazzab (2017), Moore et al. (2014)	Calculation of TRISS, Vital signs, clinical scores, ed_GCS, ed_Resp rate, ed_SBP
Ward1/2/3	Stewart et al. (2021)	Floor (medical or surgical ward)
caseloscc/loscc	Stewart et al. (2021), Moore et al. (2014)	Admission to ICU, ICU (yes or no)
mtc	Morshed et al. (2015), Moore et al. (2014)	Treated at level-1 trauma centre, Level of index trauma centre
welsh hospital	Morshed et al. (2015)	Hospitals from Northeast region
transfer type/out reason	Moore et al. (2014)	Transfer

models, which identify 'caseKnownOutcome' as a key predictor of LOS. According to the Trauma Audit & Research Network Procedures manual (The Trauma Audit & Research Network, 2023), 'outcome' refers to encompasses a patient's health status at discharge time or death, including pre-existing conditions, complications during care, outcomes at both discharge and after 30 days, dates and times of discharge or death, days intubated, and details of readmission—all of which are predominantly captured in the SWTN dataset. One possible explanation for this finding is that patients with more severe conditions often require extended hospital stays, resulting in more comprehensive documentation of outcomes. Additionally, longer hospitalisations allow for more detailed record-keeping, ensuring that outcomes are thoroughly recorded. Conversely, patients with shorter stays may not survive the early stages of hospitalisation, leading to incomplete records on physiological measurements, admissions, and discharge status. Consequently, the completeness and availability of outcome data are closely linked to the duration of a patient's stay.

5.4. Limitations

Several limitations need to be noted regarding the present study. Firstly, the current LOS models predominantly depend on clinical and demographic variables without considering socio-economic factors. Evidence suggests that socio-economic factors—including insurance type, family support, pre-injury functional status, and the capacity of rehabilitation resources—have been successfully incorporated into LOS modelling and demonstrated to significantly influence LOS (Gokhale et al., 2023; Jerath et al., 2020; Perelman & Closon, 2011). However, due to their unavailability in the current research dataset, this study was unable to explore these factors. Further refinement of the model could expand the model input, such as incorporating socio-economic, comorbidity and capacity variables. This could provide a more comprehensive LOS modelling framework while offering deeper insights into factors contributing to prolonged stays and optimising discharge planning decisions.

Secondly, although the current model framework utilised in this study (LASSO regression, RF, and GAM) mainly emphasises interpretability for identifying key LOS predictors, it may have limitations in predictive accuracy. Alternative machine learning and deep learning techniques could potentially capture more complex and nonlinear patterns in LOS variation. Future research could explore the integration of other advanced models such as ANN, XGBoost or gradient boosting, especially when more comprehensive datasets become available.

Thirdly, the generalisability of our findings is limited, as our analysis relies solely on the SWTN trauma registry dataset. Although our models and predictor selection were tailored for this particular context, their applicability to other trauma networks may be limited by regional differences in healthcare policies, patient management protocols, and data collection methods. Future research could validate these analytical methods across various trauma networks in different geographical and administrative contexts to address this limitation. The cross-network validation would evaluate the robustness and adaptability of our models while revealing universal determinants of LOS that remain consistent across different healthcare systems.

6. Conclusions

The application of statistical and machine learning models to identify driving factors for interpreting LOS in extensive trauma datasets holds promise for enhancing trauma quality assessments and optimising resource utilisation across trauma systems. This study aims to identify key driving factors capable of signalling medical staff about a potential prolonged LOS. Such insights have profound implications for managing trauma system demand, bed allocation, staffing decisions, and planning for discharge rehabilitation for individual patients.

This study paves the way for further significant research that can enhance the management of trauma networks. Future studies should aim to incorporate these social determinants or capacity variables to provide a more comprehensive interpretation of LOS. Furthermore, while the current study focuses on understanding the drivers of LOS, future work could develop probabilistic models to forecast LOS. This would require a different approach. Future research could focus on (i) developing probabilistic forecasts of LOS, (ii) predicting time to discharge with dynamic feature updates, and (iii) predicting LOS category as short, medium, and long stays.

Table 6
Detail description of variables.

Predictor	Characteristics	Descriptions	Levels
welsh incident	Categorical	Incident within Welsh postcodes areas	(1 = Yes, 0 = No)
welsh resident	Categorical	Patient's postcode classified as Welsh	(1 = Yes, 0 = No)
welsh hospital	Categorical	Welsh hospital	(1 = Yes, 0 = No)
countryid	Categorical	Country	(1 = England, 2 = Wales)
mtc	Categorical	The first admitted hospital is an MTC	(1 = Yes, 0 = No)
casemtc	Categorical	The patient was treated at an MTC during its journey in hospitals	(1 = Yes, 0 = No)
mech	Categorical	Mechanism of injury	Vehicle incident/collision, Fall less than 2 m, Blow(s) without weapon, Fall more than 2 m, Crush, Stabbing, Other, Shooting, Blow(s) with weapon, Burn, and Blast.
mechtype	Categorical	Injury type	Blunt, Penetrating
location	Categorical	Location of incident	Road, Home, Public area, Other, Other Home (not patient's), Mountain, Industrial, Segregated cycle route, Farm, Pavement/Footpath/Walkway, Institution, Air, Water, Rail track, Office.
arvmode	Categorical	Arrival mode	Ambulance, Helicopter, Car/personal vehicle, Not applicable, Other, With police, Walking, Ambulance and helicopter, Public transport, Ambulance car.
emrts	Categorical	Whether it was treated by EMRT or not	(1 = Yes, 0 = No)
age	Categorical	Age group of the patient at the moment of the incident	16–44, 65–74, 55–64, 75 and over, 45–54, Under 16.
gender	Categorical	Gender	Male, Female
wented	Categorical	Whether the patient was assessed in ED (yes/no)	(1 = Yes, 0 = No)
tteam	Categorical	Trauma team on ED	(1 = Yes, 0 = No)
msen	Categorical	Most senior doctor at ED	Consultant, FY/ST 1-2, ST 3+, ST year unknown, Associate Specialist, Other
fstdoc	Categorical	First doctor to see the patient	Consultant, FY/ST 1-2, ST 3+, ST year unknown, Associate Specialist, Other
nice	Categorical	Whether the patient fulfils the NICE head injury criteria	(1 = Yes, 0 = No)
intubvent	Categorical	Intubated/ventilated?	(1 = Yes, 0 = No)
caseintubvent	Categorical	Intubated/ventilated during all stays in hospital?	(1 = Yes, 0 = No)
pre_intubvent	Categorical	Intubated/ventilated pre-hospital?	(1 = Yes, 0 = No)
edintubvent	Categorical	Intubated/ventilated at ED?	(1 = Yes, 0 = No)
caseedintubvent	Categorical	Intubated/ventilated at ED, in any stay?	(1 = Yes, 0 = No)
ttop	Numeric	Hours to first operation (from arrival to hospital)	
caseop	Numeric	Total number of operations (all hospital stays)	
ttct	Numeric	Hours to first CT scan (from arrival to hospital)	
head	Categorical	AIS maximum severity in Head	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.

(continued on next page)

Table 6 (*continued*).

face	Categorical	AIS maximum severity in Face	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
thorax	Categorical	AIS maximum severity in Thorax	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
abdomen	Categorical	AIS maximum severity in Abdomen	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
spine	Categorical	AIS maximum severity in Spine	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
pelvis	Categorical	AIS maximum severity in Pelvis	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
limbs	Categorical	AIS maximum severity in Limbs	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
other	Categorical	AIS maximum severity external/neck	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
most_severe	Categorical	Most severely injured body region	Ordinal variable ranging from 0 to 6, where: 0: No injury dected in this area 1: Minor injuries; superficial wounds. 2: Moderate injuries; minor surgery may be required. 3: Serious injuries; potential for permanent disability, surgery likely. 4: Severe injuries; probable permanent disability, life-threatening. 5: Critical injuries; survival uncertain, critical outcomes. 6: Virtually unsurvivable; survival improbable.
outreason	Categorical	Reason for transfer out	no transfer, further specialist care, network protocol, repatriation/reverse transfer, not known, no PCCU bed, and no Critical Care bed
iss	Numeric	ISS	
ps14	Numeric	Probability of survival	
outtext	Categorical	Status on discharge	alive, Dead

(*continued on next page*)

Table 6 (*continued*).

casedied	Categorical	Did the patient died at 30 days(analysed by case)?	(1 = died, 0 = alive)
transfertype	Categorical	Type of transfer	Ordinal variable ranging from 1 to 6 (1 = No transfer, 2 = Transfer in, 3 = Transfer out, 4 = Transfer in & out, 5 = Transfer out failed, 6 = Transfer in & out failed)
txaloc	Categorical	if given tranexamic acid	Pre-hospital, ED, no test
knownoutcome	Categorical	Is the outcome known, from this hospital stay?	(1 = Yes, 0 = No)
caseknownoutcome	Categorical	Is the outcome known, from all hospital stays?	(1 = Yes, 0 = No)
ed_gcs	Numeric	Earliest GCS at ED	
ed_pulse	Numeric	Earliest pulse rate at ED	
ed_resp_rate	Numeric	Earliest respiratory rate at ED	
ed_sbp	Numeric	Earliest Systolic Blood Pressure at ED	
ct_scan	Categorical	Had a CT scan?	(1 = Yes, 0 = No)
head_operation	Categorical	Had a head operation?	(1 = Yes, 0 = No)
head_ct_scan	Categorical	Had a head ct scan?	(1 = Yes, 0 = No)
have_operation	Categorical	Had an operation	(1 = Yes, 0 = No)
rts	Numeric	Revised trauma score	
triss	Numeric	Trauma Score and Injury Severity Score	
arrival_day_of_weeks	Categorical	arrival day of weeks	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
dis-charge_day_of_weeks	Categorical	discharge day of weeks	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday
EAU	Categorical	Had been admitted to Emergency Admissions Unit	(1 = Yes, 0 = No)
Orthopaedic	Categorical	Had been admitted to Orthopaedic (include paediatric) ward	(1 = Yes, 1 = No)
Major_trauma_ward	Categorical	Had been admitted to Major Trauma ward	(1 = Yes, 2 = No)
Medical_ward	Categorical	Had been admitted to Medical(include palliative care) ward	(1 = Yes, 3 = No)
Neurosurgical rehabilitation	Categorical	Had been admitted to Neurosurgical rehabilitation ward	(1 = Yes, 4 = No)
Surgical_ward	Categorical	Had been admitted to Surgical (include paediatric) ward	(1 = Yes, 5 = No)
General_acute	Categorical	Had been admitted to General acute (include paediatric) ward	(1 = Yes, 6 = No)
Cardiothoracic	Categorical	Had been admitted to Cardiothoracic ward	(1 = Yes, 7 = No)
Spinal_injuries_unit	Categorical	Had been admitted to Spinal injuries unit	(1 = Yes, 8 = No)
Geriatric	Categorical	Had been admitted to Getiratic ward	(1 = Yes, 9 = No)
Plastic_surgery	Categorical	Had been admitted to Plastic surgery ward	(1 = Yes, 10 = No)
Maxillofacial	Categorical	Had been admitted to Maxillofacial ward	(1 = Yes, 11 = No)
CCU	Categorical	Had been admitted to Coronary Care Unit	(1 = Yes, 12 = No)
General_paediatric	Categorical	Had been admitted to General paediatric Ward	(1 = Yes, 13 = No)
PACU	Categorical	Had been admitted to Post-anaesthesia care unit	(1 = Yes, 14 = No)
Burns	Categorical	Had been admitted to Burns ward	(1 = Yes, 15 = No)
n_ward	Categorical	Total Ward Admissions per Patient	1,2,3

CRediT authorship contribution statement

Zihao Wang: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Revision. **Bahman Rostami-Tabar:** Supervision, Conceptualization, Methodology, Writing – review & editing, Project administration. **Jane Haider:** Supervision, Conceptualization, Resources, Writing – review & editing. **Javvad Haider:** Writing – review & editing. **Mohamed Naim:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Tuning parameters

In Appendix A, the process of tuning parameters for the LASSO regression (Fig. 8(a)) and Random forest models (Fig. 8(b)) are provided.

Appendix B. Predictors

In Appendix B, the common predictors utilised in the current paper and previous literature review (Table 5) and explanation of all features (Table 6) are detailed.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eswa.2025.127801.

Data availability

The authors do not have permission to share data.

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