British Journal of Hospital Medicine

Br. J. Hosp. Med. (Lond) **2026**; 87(11): 51264
https://doi.org/10.31083/BJHM51264

Article

Drivers of Hospitalization Costs in Traumatic Fracture Patients in China: A Retrospective Study Using Quantile Regression and Backpropagation Neural Networks

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Academic Editor: Livio Garattini
Submitted: 26 February 2026 Revised: 18 May 2026 Accepted: 4 June 2026 Published: 12 November 2026

Abstract

Aims/Background: Traumatic fractures (TF) impose a substantial global health and economic burden and represent a major contributor to disability and mortality, particularly in China. Understanding the determinants of hospitalization costs is essential for improving healthcare efficiency and informing cost-control strategies. This study combines quantile regression (QR) with backpropagation neural networks (BPNN) to provide a comprehensive analysis of cost drivers in patients with TF. **Methods:** Front-page data from the Zhuhai's inpatient medical records were retrospectively collected. The analytical population included 31,503 patients admitted for the treatment of traumatic fractures from 2018 to 2020. Hospitalization costs were compared across different subgroups. Subsequently, QR and BPNN methods were employed to identify the major influencing factors of hospitalization costs. **Results:** Traumatic fracture patients had a median hospital cost of ¥13,528.2 (1 Chinese Yuan [CNY] ≈ 0.149 USD) (interquartile range [IQR]: 4564.9–32,451.2). The median length of stay was 9 (IQR: 5–17). QR across the 0.1 to 0.9 quantiles revealed that age (β = 0.003–0.005, all $p < 0.001$), fracture type (lower limb, spine, other, multiple; β = 0.187–0.678, all $p < 0.001$), surgery complexity level (Levels 1–4; β = 0.114–2.020, all $p < 0.001$), comorbidity (β = 0.074–0.108, all $p < 0.001$), length of stay (β = 0.026–0.044, all $p < 0.001$), hospital grade (Grade 3 vs. Grade 2; β = 0.307–0.379, all $p < 0.001$), and payment mode (Social Medical Insurance vs. self-payment; β = 0.059–0.104, all $p < 0.001$) were significantly associated with higher hospitalization costs, while osteoporosis was associated with lower costs at higher quantiles (β = −0.108 to −0.080 [0.5 to 0.9 quantiles], $p < 0.001$). Sex showed no significant association (all $p > 0.05$). The BPNN model achieved an R^2 of 0.6556 on the test set, and identified length of stay, surgery complexity level, and hospital grade as the most important predictors. Notably, the marginal effect of length of stay increased progressively from β = 0.026 at the 0.1 quantile to β = 0.044 at the 0.9 quantile, indicating a stronger cost-driving effect among high-cost patients. **Conclusion:** QR and BPNN provided valuable insights into the factors affecting the hospitalization costs of traumatic fractures in China. The findings indicate that length of stay, surgery complexity level, and hospital grade are core predictors of these costs, and the marginal effect of length of stay increases with higher costs. Precise cost control should therefore focus on shortening hospital stays for high-cost patients, optimizing surgical grading management, and strengthening the capacity of primary-level hospitals.

Keywords: traumatic fractures; hospital costs; quantile regression; backpropagation neural network; length of stay

1. Introduction

Traumatic fractures (TF) are highly prevalent worldwide and impose a substantial economic burden. According to the Global Burden of Disease Study 2019, there were 2296.2 new fracture cases per 100,000 individuals globally, and 319.0 years lived with disability (YLDs) per 100,000 were recorded [1]. TF constitute a major cause of disability, morbidity and mortality in China [2]. Considering the heavy burden placed on healthcare systems, it is critical to investigate the economic costs associated with TF. Identifying the drivers of hospitalization costs is crucial for designing practical interventions to control and reduce relevant healthcare costs.

Previous studies have confirmed several factors influencing hospitalization costs, including length of stay, age, fracture type, and comorbidity conditions [3,4]. However, these studies are constrained by methodological limitations; particularly, the use of traditional mean-based regression approaches (e.g., ordinary least squares regression) that primarily estimate average effects may fail to capture distributional heterogeneity in cost data. Recently, quantile regression (QR) and backpropagation neural net-

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works (BPNN) have been increasingly applied in healthcare research [5,6,7,8]. Hospitalization costs are typically characterized by right-skewed distributions and heterogeneous covariate effects across different cost levels. In this context, QR offers a flexible analytical framework to explore the associations between influencing factors and outcome variables across various quantiles, without stringent requirements for data distribution assumptions [9,10,11,12]. QR was applied to analyze hospitalization costs and their associated effects [6,13,14]. Specifically, Olsen et al. [6] examined the heterogeneous effects of surgical site infections across cost quantiles; Su et al. [13] combined QR with structural equation modeling to assess the direct and indirect effects of length of stay on hospitalization costs; and Rezaei Ghahroodi et al. [14] investigated regional heterogeneity in hospitalization costs. These studies demonstrated the superiority of QR over traditional mean regression methods [15,16,17].

Nevertheless, QR is primarily a linear modeling approach and may have limited ability to capture complex non-linear relationships among variables. In contrast, neural networks, such as backpropagation neural networks (BPNN), can model complex interactions and non-linear patterns without imposing predefined functional forms [18,19,20]. Ma et al. [21] applied machine learning models to predict hospitalization costs among inpatients in China and identified the level of medical institutions, age, and length of stay as key determinants of hospitalization costs. Therefore, combining QR and BPNN provides a complementary analytical strategy: QR captures heterogeneous effects across different cost levels, while BPNN enhances the ability to model non-linear relationships and assess the relative importance of predictors. This integrated approach enables a more comprehensive understanding of hospitalization cost drivers.

This study not only aims to identify the relevant factors affecting hospitalization costs among TF patients but also to investigate whether potentially modifiable system-level factors contribute to cost escalation. Based on the above considerations, we propose three hypotheses.

Hypothesis 1: System-level factors, including hospital grade and payment method, significantly influence hospitalization costs in patients with traumatic fractures.

Hypothesis 2: The effect of length of stay on hospitalization costs varies across different cost quantiles, with stronger effects observed in higher-cost groups.

Hypothesis 3: Non-linear relationships exist between patient characteristics and hospitalization costs, which can be effectively captured using machine learning approaches such as BPNN.

2. Methods

2.1 Data Source and Study Population

We retrospectively collected front-page information from inpatient medical records from a cluster of hospitals in Zhuhai between 1 January 2018 and 31 December 2020. Only adult patients aged 18 years or older were eligible for inclusion. The sequential screening procedure used to identify traumatic fracture records is described in Section 2.2. Records with missing information on core variables or incomplete hospitalization cost data were excluded. An initial sample of 31,913 traumatic fracture records was identified. To limit the influence of extreme values, the following exclusion criteria were applied based on clinical plausibility and previous literature [22,23]: length of stay <1 day or ≥180 days (n = 27), hospitalization costs <¥100 (1 Chinese Yuan [CNY] ≈ 0.149 USD) or >¥300,000 (n = 52), and age >90 years (n = 331). The final analytical sample comprised 31,503 records.

Surgery complexity level was classified into five categories according to the "Measures for the Graded Management of Surgical Procedures in Medical Institutions" issued by the National Health Commission of the People's Republic of China: without operation (no surgical intervention), Level 1 (minor operations with low technical difficulty, simple procedures, and low risk), Level 2 (moderate operations with general technical difficulty, uncomplicated procedures, and moderate risk), Level 3 (major operations with considerable technical difficulty, complex procedures, and high risk), and Level 4 (complex major operations with high technical difficulty, very complex procedures, and extremely high risk) [24]. All clinical indicators of discharged patients were derived from the front page of medical records. The data were collected from secondary and tertiary medical institutions. Secondary hospitals provide comprehensive medical and health services, as well as regional-level teaching and research functions, with a bed capacity of 101–500. Tertiary hospitals offer high-level specialized medical services across multiple regions, undertake advanced medical education and research responsibilities, and possess more than 500 beds. The front sheets of inpatient medical records contain abundant clinical information, covering demographic characteristics, primary and secondary diagnoses, procedures, length of stay, hospital grade, and method of payment. Variable selection was conducted based on a three-dimensional integrated approach: (1) clinical relevance: screening variables that are recognized as key factors affecting traumatic fracture hospitalization costs in orthopedic and trauma clinical practice (e.g., age, fracture type, operation level); (2) existing literature evidence: incorporating core predictors validated in previous studies on hospitalization costs for musculoskeletal and traumatic diseases; (3) univariate analysis ($p < 0.05$): a supplementary preliminary screening to exclude variables with no statistical correlation with the outcome. The final nine covariates selected are all clinically meaningful core variables in the field of TF research, and no variables with major clinical significance for TF hospitalization costs were omitted. The length of stay refers to the duration for which the patients received inpatient treatment. Age was treated as

a continuous variable (in years) in the QR analysis to preserve granularity and statistical power. Participants were stratified by age into six brackets: 18–34, 35–44, 45–54, 55–64, 65–74, and ≥75 years. Sex was classified as male or female. Fracture types were categorized into lower limb, upper limb, spinal, other single-site, and multiple fractures. Hospitals were stratified into tertiary and secondary levels.

The quantile points of the dependent variable (hospitalization cost, log-transformed) were set at 0.1, 0.3, 0.5, 0.7, and 0.9. These quantiles were chosen to fully reflect the heterogeneous impacts of covariates across the full cost spectrum, ranging from low-cost patients at the 10th percentile to high-cost individuals at the 90th percentile. The median (50th percentile) represents the typical cost level, while the 30th and 70th percentiles provide intermediate information. This set of quantiles has been applied in healthcare cost research; for example, Zhao et al. [25] used the same quantiles (0.1, 0.3, 0.5, 0.7, and 0.9) in analyzing medical expenditure data to fully reflect the varied impacts of influencing factors at different cost levels.

2.2 Definition of Traumatic Fractures

Traumatic fracture records were identified through a sequential screening procedure based on ICD-10 codes and diagnosis text. First, records with ICD-10 codes S00–S99 or T00–T35 and trauma recorded as the primary diagnosis were identified. These code ranges were used for initial screening and were not considered sufficient to identify traumatic fractures. Second, among these records, those with diagnosis text containing the term "fracture" were retained. Records referring to skull fractures, old fractures, or cartilage fractures, as well as admissions solely for removal of internal fixation devices following fracture healing, were excluded. Patients undergoing internal fixation for treatment of a current traumatic fracture were not excluded on the basis of that procedure. Third, only records with traumatic fracture recorded as the primary diagnosis were considered eligible for inclusion; non-fracture primary diagnoses did not qualify. The additional eligibility and exclusion criteria described in Section 2.1 were applied to obtain the final analytical sample [26].

2.3 Statistical Methods

We first assessed the normality of continuous variables (hospitalization cost, age, and length of stay) using the Kolmogorov–Smirnov test. The results indicated that all continuous variables significantly deviated from normality ($p < 0.001$), suggesting hospitalization costs presented a right-skewed pattern. Therefore, continuous data were presented as median and interquartile range (IQR). Descriptive statistical analyses were performed, and intergroup differences in inpatient expenses were examined using either the Mann–Whitney U test or Kruskal–Wallis H test accordingly. Hospitalization costs were log-transformed and subsequently incorporated into the QR model as the dependent variable.

Variable selection was primarily based on clinical relevance and existing literature evidence, with univariate analysis ($p < 0.05$) used as a supplementary screening criterion. A total of nine factors were screened and included as independent variables (X): sex, age, type of fracture, osteoporosis, surgery complexity level, comorbidity, length of stay, hospital grade, and payment mode. The quantiles of the outcome variable—hospitalization cost (Y)—were divided into five levels from 0.1 to 0.9 at an interval of 0.2. Prior to QR analysis, the outcome variable was logarithmically transformed.

Before BPNN model training, continuous independent variables, including age and length of stay, were standardized using Z-score normalization (mean = 0, standard deviation = 1) to ensure comparable scales across input features and to improve the stability and robustness of the BPNN model training process. Besides, we also performed a logarithmic transformation on the skewed hospitalization cost data to stabilize variance and meet the assumptions of the BPNN model. The selection of BPNN over other machine learning methods, such as random forests or gradient boosting, was motivated by its superior performance in handling continuous outcome variables and capturing complex nonlinear patterns within structured administrative data. Unlike ensemble models that often function as "black boxes", BPNN provides a transparent mechanism for assessing feature importance through gradient-based sensitivity analysis. This ensures a balance between high predictive accuracy and the model transparency required for healthcare policy evidence. In the neural network training phase, input data were combined with model weights that were optimized through backpropagation. The Root Mean Squared Propagation (RMSProp) optimizer and squared error loss function were adopted for model iteration. The BPNN model in this study comprises three hidden layers with 4, 8, and 16 neurons, respectively. The number of neurons in the three hidden layers (4, 8, 16) was determined through exploratory experiments and performance comparison. Multiple network configurations were tested to minimize prediction error and avoid overfitting. The final 4-8-16 structure was selected for its superior generalization performance on the validation dataset. The Rectified Linear Unit (ReLU) was selected as the activation function to facilitate nonlinear mapping for predictions. To mitigate overfitting, several measures were implemented, including an 80%/20% training-test split, validation loss monitoring, and selecting model parameters based on the minimum validation loss rather than the final training epoch. The BPNN model was trained over 300 epochs on a randomly sampled 80% portion of the dataset to ensure convergence stability; however, the final model weights were captured at the point of the lowest validation loss. Feature importance was quantified using gradient-based sensitivity analysis. This method has

been previously validated in neural network interpretation studies [27,28]. Feature importance was derived from the normalized gradients of each input variable relative to the predictions, averaged across the test set. This metric represents the relative contribution of each variable to the predictive outcome rather than absolute effects or causal relationships, and the values were standardized to facilitate comparison. The structure of our developed model is presented in Fig. 1.

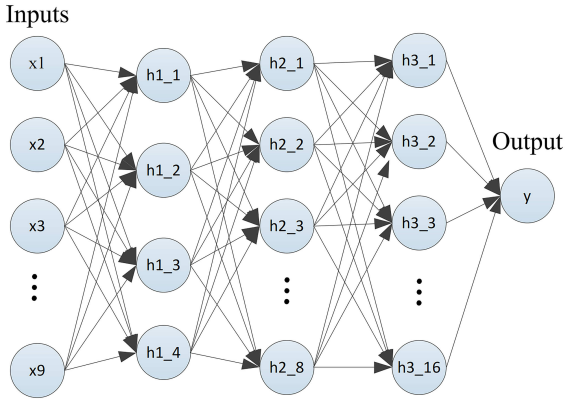


Fig. 1. Schematic structure of the proposed BPNN model. Xs represent the input variables, Hs stand for the neuron units within hidden layers, while Y indicates the output corresponding to hospitalization costs.

All statistical analyses were performed using SAS 9.4 software (SAS Institute, Cary, NC, USA). Data visualization and figure plotting were performed using Python 3.6 (Python Software Foundation, Wilmington, DE, USA) and Keras 2.2.5 (Google Inc., Mountain View, CA, USA). A two-sided *p*-value of 0.05 was adopted as the cutoff for statistical significance.

3. Results

3.1 Patient Characteristics and Cost Distribution

A total of 31,503 patients with a confirmed diagnosis of traumatic fracture were included for analysis, all of whom were hospitalized in a cluster of hospitals in Zhuhai during the period spanning 2018 to 2020. The median (IQR) age of the fracture patients was 50 (38, 62) years, with 63.1% being male. The median (IQR) length of stay was 9 (5, 17) days. A total of 23,433 patients (74.4%) underwent surgery. The median (IQR) hospitalization cost for fracture treatment was ¥13,528.2 (4564.9, 32,451.2).

3.2 Univariate Analysis of Hospitalization Costs

Univariate analysis revealed that the hospitalization costs of TF patients differed markedly by sex, age groups, fracture type, presence of osteoporosis, surgery complexity levels, comorbidity status, length of stay, hospital grade, and payment mode ($p < 0.001$), as summarized in Table 1.

3.3 Quantile Regression Analysis

Table 2 presents the QR findings for hospitalization expenses among TF patients. QR analysis indicated that advanced age, more severe types of fracture, surgery complexity level, comorbidity, longer length of stay, higher grade of hospitals, and payment with Social Medical Insurance were all significantly linked to increased inpatient costs across the 0.1 to 0.9 quantile range. The length of hospital stay exhibited a more pronounced correlation with rising hospitalization costs in the upper quantile range relative to the lower quantiles. Conversely, fracture type and comorbidity exerted a stronger influence on hospitalization costs at lower quantiles compared with higher quantiles. Surgical intervention exerted a greater influence on the distribution of hospitalization costs at lower quantiles than at higher quantiles, and this pattern remained consistent across all four surgical levels (Levels 1–4). The quantile regression analysis revealed a critical shift in the impact of length of stay. While length of stay was significantly associated with costs across all levels, its coefficient intensified from 0.026 at the 0.1 quantile to 0.044 at the 0.9 quantile. This indicates that for every unit increase in length of stay, the rate of cost escalation is substantially higher for patients already in the high-cost category. For sex, female patients showed slightly higher coefficients than male patients across all quantiles, but none of these associations reached statistical significance ($p > 0.05$ for all quantiles), suggesting that sex was not an independent driver of hospitalization costs in this patient population. Regarding osteoporosis, patients with osteoporosis exhibited negative coefficients at higher quantiles ($\beta = -0.080$ at Quantile 0.5, –0.075 at Quantile 0.7, and –0.108 at Quantile 0.9, all $p < 0.001$), indicating lower hospitalization costs compared to those without osteoporosis after adjusting for other covariates.

3.4 BPNN Model Performance

Table 3 presents the predictive performance of the BPNN model for hospitalization costs. The BPNN model achieved an R-squared value of 0.6556 on the test set, indicating it explains approximately 65.6% of the variance in hospitalization costs. This explanatory power is considered highly satisfactory given the inherent heterogeneity and stochasticity of medical administrative data. Furthermore, the comparable mean square error (MSE) and mean absolute error (MAE) values between the training and test sets demonstrate robust generalization and minimal overfitting.

Fig. 2 represents the training and validation loss curve of the BPNN model. The vertical axis shows the loss value, calculated using the MSE loss function, and the horizontal axis represents the training epochs. The change in the training loss over time reflects convergence using the training set, while the validation loss over time demonstrates generalization using the validation set. Both training and validation loss significantly decreased until the 15th epoch, where

Table 1. Results of univariate analyses on the hospitalization cost.

Variables	N (%)	Hospitalization cost in CNY		
		Median (IQR)	Z/H	*p*-value
Sex			–15.36	<0.001
Male	19,880 (63.1)	11,249.7 (4246.2, 30,269.5)		
Female	11,623 (36.9)	18,527.0 (5265.7, 35,389.1)		
Age (years)			1028.89	<0.001
18–34	6018 (19.1)	10,160.2 (3649.4, 26,624.0)		
35–44	5173 (16.4)	10,494.8 (4020.4, 28,282.2)		
45–54	8121 (25.8)	10,779.0 (4205.4, 30,256.5)		
55–64	5396 (17.1)	13,629.3 (4681.7, 32,545.9)		
65–74	3159 (10.0)	20,918.7 (6629.3, 37,722.7)		
≥75	3636 (11.5)	25,177.2 (8210.7, 43,813.4)		
Type of fracture			2349.39	<0.001
Lower limb	8371 (26.6)	23,415.5 (5901.4, 42,391.4)		
Upper limb	7075 (22.5)	8202.4 (3742.8, 20,598.1)		
Spine	4964 (15.8)	6787.3 (3675.6, 17,397.2)		
Others	5342 (17.0)	17,726.1 (5564.8, 34,831.4)		
Multiple fractures	5751 (18.3)	22,333.8 (5713.6, 41,648.5)		
Osteoporosis			15.53	<0.001
Yes	1590 (5.0)	22,686.5 (12,364.6, 34,432.9)		
No	29,913 (95.0)	12,717.6 (4340.0, 32,247.4)		
Surgery complexity level			18,451.46	<0.001
Without operation	8070 (25.6)	4586.1 (2672.4, 7675.2)		
Level 1	5313 (16.9)	3943.7 (2464.9, 7016.7)		
Level 2	1656 (5.3)	6978.4 (4024.3, 14,889.1)		
Level 3	12,881 (40.9)	28,579.4 (17,310.0, 44,523.5)		
Level 4	3583 (11.4)	37,942.8 (23,849.1, 60,945.8)		
Comorbidity			26.11	<0.001
Yes	8658 (27.5)	20,663.3 (6496.8, 39,772.6)		
No	22,845 (72.5)	11,184.3 (4061.0, 29,481.2)		
Length of stay (days)			13,688.72	<0.001
≤7	12,743 (40.5)	4164.3 (2437.0, 10,429.7)		
8–14	8415 (26.7)	15,525.2 (6665.8, 28,756.5)		
15–28	7387 (23.4)	32,913.6 (16,951.3, 50,388.7)		
>28	2958 (9.4)	48,881.1 (24,547.5, 79,274.4)		
Hospital grade			–55.27	<0.001
Grade 2	11,410 (36.2)	6282.5 (3112.5, 19,678.1)		
Grade 3	20,093 (63.8)	20,389.8 (6679.5, 39,244.8)		
Payment mode			550.33	<0.001
Social Medical Insurance	10,172 (32.3)	19,916.9 (6335.2, 35,641.2)		
Self-payment	18,528 (58.8)	10,154.6 (3970.9, 29,969.7)		
Others	2803 (8.9)	15,343.5 (5035.8, 33,992.5)		

Notes: IQR, interquartile range. *p*-values testing difference between subgroups were compared by Mann–Whitney *U* test or Kruskal–Wallis *H* test, as appropriate. 1 CNY ≈ 0.149 USD.

the model tends to converge. We implemented 300 epochs to obtain stable model weights and chose the minimum validation loss as the best weights for the hospitalization cost regression model.

3.5 Feature Importance Analysis

Fig. 3 illustrates the feature importance rankings for hospitalization cost prediction derived from the BPNN model. It is evident that length of stay, surgery complexity level, and hospital grade ranked as the three most influential determinants of inpatient cost, with corresponding importance scores of 0.963, 0.886 and 0.447. Among all predictors, the length of stay exerted the strongest effect on overall hospitalization cost.

Table 2. Quantile regression analysis of factors associated with log-transformed hospitalization costs in patients with traumatic fractures.

Variables	0.1 quantile β (*p*)		0.3 quantile β (*p*)		0.5 quantile β (*p*)		0.7 quantile β (*p*)		0.9 quantile β (*p*)	
Sex (reference: male)										
Female	0.007	(0.618)	0.002	(0.833)	0.001	(0.881)	0.004	(0.588)	0.014	(0.158)
Age (years)	0.004	(<0.001)	0.005	(<0.001)	0.005	(<0.001)	0.004	(<0.001)	0.003	(<0.001)
Type of fracture (reference: upper limb)										
Lower limb	0.460	(<0.001)	0.373	(<0.001)	0.281	(<0.001)	0.199	(<0.001)	0.187	(<0.001)
Spine	0.678	(<0.001)	0.531	(<0.001)	0.416	(<0.001)	0.341	(<0.001)	0.311	(<0.001)
Others	0.560	(<0.001)	0.478	(<0.001)	0.419	(<0.001)	0.357	(<0.001)	0.352	(<0.001)
Multiple fractures	0.506	(<0.001)	0.455	(<0.001)	0.369	(<0.001)	0.284	(<0.001)	0.271	(<0.001)
Osteoporosis (reference: no)										
Yes	–0.037	(0.237)	–0.061	(0.06)	–0.080	(<0.001)	–0.075	(<0.001)	–0.108	(<0.001)
Surgery complexity level (reference: without operation)										
Level 1	0.310	(<0.001)	0.156	(<0.001)	0.114	(<0.001)	0.120	(<0.001)	0.161	(<0.001)
Level 2	0.972	(<0.001)	0.760	(<0.001)	0.701	(<0.001)	0.736	(<0.001)	0.922	(<0.001)
Level 3	1.857	(<0.001)	1.687	(<0.001)	1.658	(<0.001)	1.641	(<0.001)	1.595	(<0.001)
Level 4	2.020	(<0.001)	1.742	(<0.001)	1.724	(<0.001)	1.727	(<0.001)	1.754	(<0.001)
Comorbidity (reference: no)										
Yes	0.107	(<0.001)	0.108	(<0.001)	0.097	(<0.001)	0.087	(<0.001)	0.074	(<0.001)
Length of stay (per day increase)	0.026	(<0.001)	0.033	(<0.001)	0.037	(<0.001)	0.040	(<0.001)	0.044	(<0.001)
Hospital grade (reference: grade 2)										
Grade 3	0.379	(<0.001)	0.314	(<0.001)	0.314	(<0.001)	0.307	(<0.001)	0.314	(<0.001)
Payment mode (reference: self-payment)										
Social Medical Insurance	0.104	(<0.001)	0.078	(<0.001)	0.074	(<0.001)	0.059	(<0.001)	0.062	(<0.001)
Others	–0.074	(<0.001)	–0.099	(<0.001)	–0.129	(<0.001)	–0.148	(<0.001)	–0.143	(<0.001)
Pseudo R^2	0.468		0.543		0.571		0.551		0.510	

Notes: β represents the coefficient from the quantile regression model using log-transformed hospitalization costs. Since the dependent variable was log-transformed, β indicates the percentage change in hospitalization costs for a one-unit change in the independent variable. All models were adjusted for the variables listed in the table.

Table 3. The performance of the backpropagation neural network (BPNN) model.

	R^2	MAE	MSE (million)	RMSE
Training set	0.6638	10,945	422.25	20,548
Test set	0.6556	10,621	376.54	19,404

Notes: R^2, R-squared; MAE, Mean Absolute Error; MSE, Mean Square Error; RMSE, Root Mean Square Error. All indicators are calculated based on the original CNY unit of hospitalization cost.

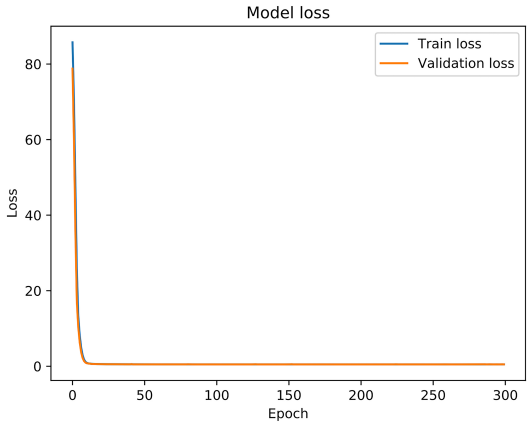


Fig. 2. The training and validation loss curves of the backpropagation neural network (BPNN) regression model. The loss value is calculated based on the log-transformed hospitalization cost; the model converges at the 15th epoch with the minimum validation loss.

4. Discussion

To contain the rising medical costs and safeguard high-quality healthcare services, China has introduced a host of medical reform initiatives over recent years. This study showed that TF patients had a median hospitalization expense of ¥13,528.2, with a median length of hospital stay of 9 days (IQR: 5–17 days). We adopted quantile regression (QR) and neural network models to explore the key factors affecting hospitalization expenses among TF

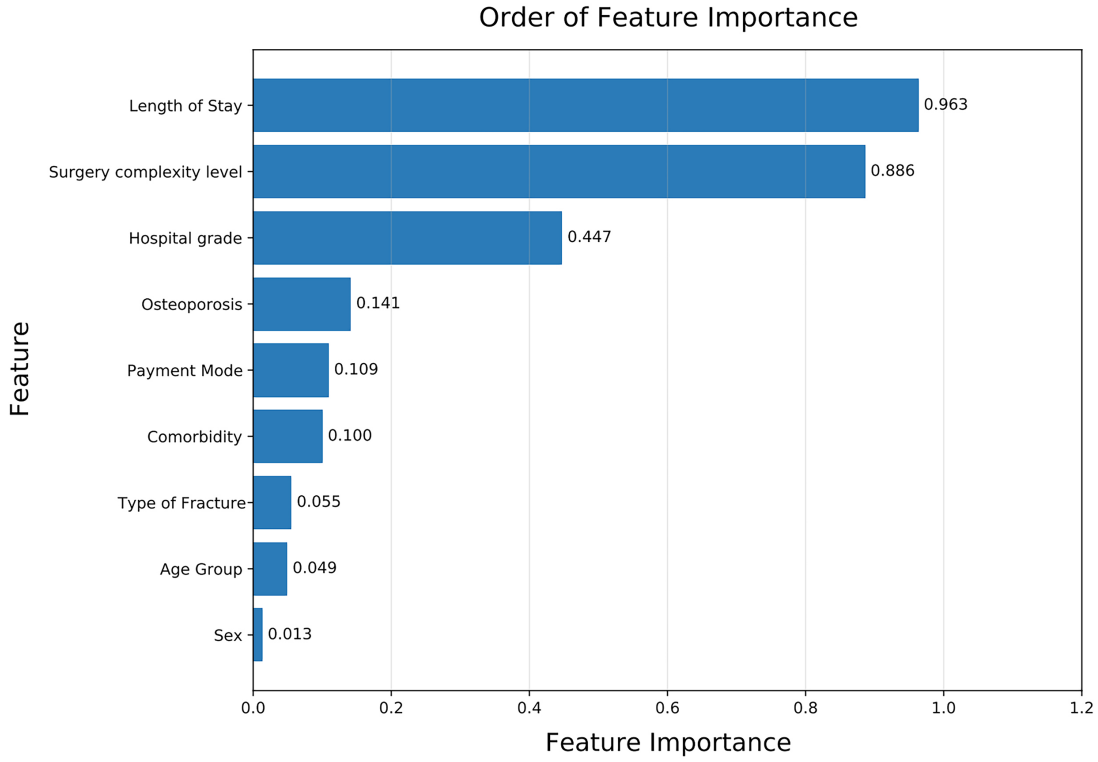


Fig. 3. Contributions of input features to the prediction of hospitalization costs, ordered from the most important (at top, length of stay) to the least important (at bottom, sex).

patients. QR results indicated that older age, more severe fracture types, undergoing operation, presence of comorbidities, longer length of stay, higher-grade hospital, and coverage by Social Medical Insurance were all significantly correlated with increased medical costs. In addition, the machine learning model further identified the length of stay, surgery complexity level, and hospital grade as the three most influential predictors of inpatient expenditure.

While the positive correlation between length of stay and hospitalization costs is well-documented [13,29], our study adds a novel dimension by uncovering the heterogeneous nature of this relationship. Instead of a uniform impact, we found that the economic burden of prolonged length of stay is disproportionately magnified in high-cost cases. This suggests that "one-size-fits-all" policies to reduce length of stay may be less effective than targeted interventions for patients at the upper end of the cost distribution. By identifying this escalating marginal effect, our findings provide a more nuanced evidence base for DRG/DIP reforms, emphasizing that cost-control efforts should prioritize the management of high-resource-consuming outliers. The present study also found that advanced age is linked to elevated hospitalization expenses, which aligns well with the findings of prior research [30,31]. This may be attributed to the fact that older individuals are more prone to comorbidities and consequently need more sophisticated medical services [32]. Moreover, this study found that fracture location was correlated with increased hospitalization costs. This finding is consistent with existing evidence and underscores the importance of precise diagnosis and individualized treatment for various fracture categories [33]. Therefore, strengthening the operational efficiency and service quality of primary and grassroots hospitals may help lower the hospitalization expenditure of TF patients. In the QR analysis, osteoporosis was associated with lower hospitalization costs at several cost quantiles. This finding should not be interpreted as a protective or cost-reducing effect of osteoporosis. After controlling for length of stay, fracture type, surgical intervention, comorbidities, and hospital grade, osteoporosis may act as a proxy for a subgroup of patients who predominantly experience low-energy fractures and consequently receive less intensive treatment. Compared with patients suffering from high-energy trauma or multiple injuries, these patients are less likely to require complex surgical procedures, high-cost medical consumables, or intensive care. Similar conditional negative associations have been reported in previous orthopedic cost studies.

The neural network model in our study further demonstrated that the length of stay, surgery complexity level and hospital grade emerged as the dominant determinants of inpatient expenditure. Machine learning techniques have also been widely adopted in orthopedics for cost prediction across multiple procedures, including total hip and knee arthroplasty, total shoulder replacement, and spinal fusion surgery [34,35,36,37]. Karnuta et al. [36] constructed a ma-

chine learning algorithm to forecast total medical expenses, discharge outcomes, and hospital stay duration after shoulder arthroplasty using data from the National Inpatient Sample database. It is suggested that properly reducing hospitalization length on the premise of ensuring treatment effect plays a vital role in cutting down medical costs. Besides, the financial pressure on patients can be greatly eased by three measures: reinforcing the gatekeeping function of primary care, cutting waiting time before surgery, and delegating postoperative rehabilitation services to grassroots primary care institutions [8].

In the context of China's ongoing diagnosis-related groups (DRG) and diagnosis–intervention packet (DIP) payment reforms, our findings have important policy implications. Both DRG and DIP adopt prospective payment mechanisms that place strong incentives on hospitals to control resource utilization, particularly length of stay and treatment intensity. Our results demonstrate that length of stay remains the dominant driver of hospitalization costs across cost quantiles, especially among high-cost patients, suggesting that effective management of inpatient days is central to achieving cost containment under prospective payment systems.

Moreover, the significant association between hospital grade and hospitalization costs reflects persistent differences in service intensity and case complexity between tertiary and secondary hospitals. This finding is consistent with our earlier results and underscores the importance of hierarchical healthcare delivery systems. This finding supports ongoing efforts to promote hierarchical medical systems and rational patient referral, whereby patients with stable or less complex fractures could be appropriately treated at lower-level hospitals, thereby improving overall healthcare system efficiency. Taken together, our results provide empirical evidence that optimizing length of stay, aligning treatment intensity with clinical severity, and strengthening tiered healthcare delivery are key levers for enhancing the effectiveness of DRG/DIP payment reforms in China.

5. Limitation

Several limitations of the present research should be acknowledged. Firstly, as the study sample was sourced from one single area, the conclusions might not be fully applicable to other groups or healthcare settings. Secondly, the selection of predictor variables in this analysis was restricted by the research objectives and available data resources. Some potential influencing factors associated with hospitalization costs may therefore not have been incorporated into the model. Thirdly, although the BPNN model was employed to explore non-linear relationships in hospitalization cost data, a traditional statistical approach, such as Generalized Linear Models (GLM) or Ordinary Least Squares (OLS) regression, was not constructed as a formal baseline comparator. In health economics and cost-related research, GLM is widely recognized as a standard method for modeling skewed cost outcomes and serves as a common benchmark for evaluating predictive performance. Future studies aiming to validate the application of neural networks in cost prediction are strongly encouraged to incorporate GLM or other generalized linear modeling frameworks as reference models. Finally, the present research only concentrated on direct inpatient costs and failed to address other economic burdens of TF, including indirect medical costs and productivity loss. Subsequent research may incorporate more influencing variables to further validate the model, and formulate targeted, refined strategies to efficiently contain and lower hospitalization costs for TF patients.

6. Conclusion

Overall, this study offers valuable insights into hospitalization costs among TF patients in China. The analysis revealed that the length of stay, surgery complexity level, and hospital grade are the core factors associated with hospitalization-related expenditures. These findings may offer practical guidance for healthcare administrators and policymakers in China to formulate targeted strategies to control and reduce hospitalization costs among TF patients. Further research ought to explore additional determinants associated with TF-related costs and develop effective strategies to alleviate the economic burden associated with this major public health challenge.

Key Points

• The median inpatient expenditure of TF patients was ¥13,528.2, with a median hospital stay of 9 days. Length of stay, surgery complexity level, and hospital grade were identified as the top three factors affecting medical costs.

• The marginal effect of length of stay on hospitalization costs increased progressively from lower to higher cost quantiles ($\beta = 0.026$ at the 0.1 quantile to $\beta = 0.044$ at the 0.9 quantile), revealing a heterogeneous impact that is more pronounced among high-cost patients.

• Our findings suggest that targeted interventions aimed at reducing length of stay, optimizing surgical grading management, and strengthening the capacity of secondary-level hospitals could help alleviate the economic burden among patients with traumatic fractures in China.

Availability of Data and Materials

The datasets used and analyzed during the current study are available from the corresponding author on request.

Author Contributions

PL, HJ and YQ conceived and designed this project; PL, ZY and HJ contributed to data collection; LZ, XG, ZY, XL and ZL contributed to data analysis; PL wrote the manuscript with input and revision from all authors. All authors contributed to revising the manuscript critically for

important intellectual content, read and approved the final manuscript, and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Zhuhai People's Hospital (Approval No. ZYEC [R] 2023-034). Owing to the retrospective design of the study and the use of fully anonymized data with no identifying personal information, the requirement for informed consent was waived by the Ethics Committee of Zhuhai People's Hospital.

Acknowledgment

Not applicable.

Funding

This study was indirectly supported by the National Natural Science Foundation of China (Grant Nos. 82174142 to YQ), the Guangdong Natural Science Foundation of China (Grant Nos. 2021A1515410001 to YQ).

Conflicts of Interest

The authors declare no conflicts of interest.

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