Identify hospitalization cost drivers of traumatic fracture patients in China using quantile regression and backpropagation neural network

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Research Article

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Abstract

Objective

Analyze the factors associated with hospitalization costs of traumatic fracture patients.

Methods

Data for the retrospective analysis was extracted from the first pages of inpatient medical records in Zhuhai, China. The sample consisted of 31503 patients hospitalized for traumatic fractures between January 1, 2018 and December 31, 2020. We first compared differences in hospitalization costs between subgroups, followed by quantile regression and backpropagation neural network to investigate the key drivers of the hospitalization costs.

Results

The median hospitalization cost for traumatic fracture patients was ¥13528.2. The mean length of stay was 13.77 days. Quantile regression showed that higher hospitalization costs from the Quantile 0.1 to the Quantile 0.9 significantly correlated with advanced age, more severe types of fracture, operation, comorbidity, longer length of stay, higher level of hospital, and payment with Medicare. Backpropagation neural network indicated that the length of stay, operation level and hospital level were the most important predictors of hospitalization costs.

Conclusion

Quantile regression and backpropagation neural network yielded valuable information on the factors affecting the hospitalization costs of traumatic fractures in China. Findings suggested that interventions aiming to reduce length of stay contributed to reducing the economic burden associated with traumatic fractures.

Introduction

Traumatic fractures (TF) are costly while globally prevalent. Global burden of disease 2019 study estimated that there were 2296.2 new incident cases of TF and 319.0 years of life lost per 100,000 population worldwide in 2019[1]. In China, TF account for a significant portion of disability, morbidity, and mortality[2]. This major healthcare burden necessitates the study on its medical costs, which further motivated the identification of hospitalization cost drivers for developing effective strategies to manage and reduce these costs.

Several factors were identified to influence hospitalization costs in previous studies, including length of stay, age, type of fracture, and comorbidity [3–4]. There, however, were certain methodological flaws which called the application of advanced techniques to produce more interpretable and nuanced interpretations. Recently, quantile regression (QR) and backpropagation neural network (BPNN) has been applied to shed such light on healthcare studies [5–8]. QR models relationship between predictors and the response variable across different quantiles without strict normal distributional assumptions like ordinal least square regression, providing more nuanced understanding of the data, especially when data distribution is heavily skewed with outliers [9–12]. Olsen *et al*. [6], Su *et al*. [13], and Rezaei *et al*. [14] applied QR to analyze the hospitalization costs and its direct and in direct effects. These studies showed the superiority of QR compared to canonical statistical methods.[15–17] Despite its strength, QR offered little information on the importance of different feature on the model prediction, where neural network could contribute. Neural network can capture complex relationships between variables and produce accurate predictions without imposing any specific functional form on the data.[18–20] Zhang *et al*. [21] use the neural network to analyze the influencing factors of hospitalization costs of breast cancer patients in a tertiary hospital and the results showed the number of operations and actual hospitalization days were the important influencing factors. The combined use of two methods will provide more nuanced and profound understandings. To our knowledge, no previous studies have used QR together with BPNN to analyze the hospitalization costs of TF patients in China. This study aimed to analyze the hospitalization cost of TF patients in China using QR and BPNN. Specifically, we aimed to identify the predictors of hospitalization cost. Our findings were expected to provide insights into the management and reduction of hospitalization costs for TF patients in China.

Methods

2.1 Data source and study population

Our research was in compliance with the Helsinki Declaration approved by the ethics committee of Zhuhai People's Hospital. We extracted the first pages of every inpatient medical record from January 1, 2018 to December 31, 2020 in Zhuhai, China (total $N = 31913$). All discharged patient variables were obtained from the first page of medical records, which were collected in Grade 2 medical and health institutions (secondary level, providing comprehensive medical and health services and undertaking certain teaching and research tasks of regional hospitals with 101–500 beds) and Grade 3 medical and health institutions (ternary level, providing high level specialized medical and health services to several regions along with higher education and research tasks in regional hospitals with > 500 beds). The first pages of inpatient medical records provided: demographic characteristics, primary and secondary diagnoses, procedures, length of stay, level of hospital, and method of payment. 74 variables were extracted in total. We excluded patients who had missing data on any of the key variables or hospitalization cost. To avoid extreme values in hospitalization costs, we excluded 27 observations with the length of stay < 1 day or ≥ 180 days, 52 observations with hospitalization costs < ¥100 or > ¥300,000, and 331 observations aged > 90 years. Length of stay was defined as the number of days the patient stayed in the hospital. Age was categorized into six groups: < 35, 35–44, 45–54, 55–64, 65–74, and ≥ 75 years. Sex was coded as male or female. Types of fracture were classified into lower limb, upper limb, spine, other, or multiple fractures. Levels of hospital included tertiary and secondary.

2.2 Definition of traumatic fractures

According to the International Classification of Diseases 10th Revision (ICD-10), traumas were defined as ICD-10 diagnosis code S00-S99 and T00-T35.. Inpatients with a primary diagnosis of trauma were defined as inpatients with a trauma. Diagnoses with the word “fracture” were selected, while diagnoses such as “skull fracture”, “old fracture”, “cartilage fracture” and “internal fixation of fracture” were excluded. Inpatients with a primary diagnosis of TF were defined as inpatients with a TF.

2.3 Statistical methods

As hospitalization costs followed a skewed distribution, we described these data as a median with interquartile range (IQR). Summary statistics were generated, and the differences of hospitalization cost between subgroups were compared by Mann–Whitney *U*-test or Kruskal–Wallis *H*-test, as appropriate. The hospitalization costs were taken logarithmically and then included in the QR model as a dependent variable. We performed variable selection by means of univariable analysis with the inclusion criteria of 0.05. Nine variables were selected, including gender, age, type of fracture, osteoporosis, operation level, comorbidity, length of stay, hospital level, and payment mode, which were set as the independent variable X; the quantile point of the explained variable hospitalization cost (Y) was divided into 5 sections, ranging from 0.1 to 0.9, with an interval of 0.2. Outcome variable was log transformed for QR analysis.

In addition, BPNN was carried out with the input variables as the factors selected above and the output variable as log-transformed hospitalization cost. During network training, inputs were multiplied by weights tuned with backpropagation, with the RMSprop optimizer and the squared error loss function. The model consisted of three hidden layers with four, eight, and sixteen neurons respectively. We chose rectified linear unit as the activation function for resolving predictions via nonlinear process. The BPNN was trained with 300 epochs on randomly selected 80% of the dataset and tested on the remaining 20%. Figure 1 showed the structure of our model.

Data analyses were carried out using SAS 9.4 (SAS Institute, Cary, NC). Figures were generated with Python 3.6 and Keras 2.2.5 Threshold for statistical significance was set as 0.05 for two-sided *P* values.

Results

In this study, we analyzed 31,503 patients diagnosed as TF and hospitalized in Zhuhai between January 1, 2018 to December 31, 2020. The mean (SD) age of the fracture patients was 51.06 (16.96) years, with 63.1% of the male. The mean (SD) length of stay was 13.77 (14.91) days. 23,433 patients (74.4%) underwent surgery. The median (IQR) cost of the hospital admission with the fracture was ¥13,528.2 (4,564.9, 32,451.2). Pearson's correlation analysis among the hospitalization costs, age and the length of stay was performed to find that there existed correlation-ship.

Univariate analysis showed that the hospitalization costs of TF patients differed significantly among different sex, age groups, types of fracture, patients with or without osteoporosis, operation levels, patients with or without comorbidity, the length of stay, hospital levels, and payment modes ($P < 0.001$), as shown in Table 1. Table 2 describes the results of QR analysis of hospitalization costs for TF patients. QR showed that advanced age, more severe types of fractures, operation, comorbidity, longer length of stay, higher levels of hospital and payment with Medicare were significantly associated with higher hospitalization costs from the Quantile 0.1 to the Quantile 0.9. The results suggested that the length of stay is more obviously associated with greater hospitalization costs at the upper than lower quantiles (β = 0.026 for Quantile 0.1, β = 0.04 for Quantile 0.9). The effects of fracture type and comorbidity on hospitalization costs were greater at the lower than upper quantiles. The distribution of hospitalization costs at the lower quantiles was more impacted by surgery than at the higher quantiles, regardless of operations at the 1, 2, 3, and 4 levels.

Table 1
Results of univariate analyses on the hospitalization cost.

Variables	N (%)	Hospitalization cost, RMB		
		Median (IQR)	*Z/H*	*Pp*-value
Gender			-15.36	< 0.001
Male	19880 (63.1)	11249.7 (4246.2, 30269.5)		
Female	11623 (36.9)	18527.0 (5265.7, 35389.1)		
Age, y				
18 ~ 34	6018 (19.1)	10160.2 (3649.4, 26624.0)	1028.89	< 0.001
35 ~ 44	5173 (16.4)	10494.8 (4020.4, 28282.2)		
45 ~ 54	8121 (25.8)	10779.0 (4205.4, 30256.5)		
55 ~ 64	5396 (17.1)	13629.3 (4681.7, 32545.9)		
65 ~ 74	3159 (10.0)	20918.7 (6629.3, 37722.7)		
≥ 75	3636 (11.5)	25177.2 (8210.7, 43813.4)		
Type of fracture			2349.39	< 0.001
Lower Limb	8371 (26.6)	23415.5 (5901.4, 42391.4)		
Upper Limb	7075 (22.5)	8202.4 (3742.8, 20598.1)		
Spine	4964 (15.8)	6787.3 (3675.6, 17397.2)		
Other	5342 (17.0)	17726.1 (5564.8, 34831.4)		
Multiple fracture	5751 (18.3)	22333.8 (5713.6, 41648.5)		
Osteoporosis			15.53	< 0.001
Yes	1590 (5.0)	22686.5 (12364.6, 34432.9)		
No	29913 (95.0)	12717.6 (4340.0, 32247.4)		
Operation level			18451.46	< 0.001
Without	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, 14889.1)		
Level 3	12881 (40.9)	28579.4 (17310.0, 44523.5)		
Level 4	3583 (11.4)	37942.8 (23849.1, 60945.8)		
Comorbidity			26.11	< 0.001

Notes: IQR, interquartile range. *P*-value testing difference between subgroups were compared by Mann–Whitney U-test or Kruskal–Wallis H-test, as appropriate.

Variables	N (%)	Hospitalization cost, RMB		
		Median (IQR)	*Z/H*	*Pp*-value
Yes	8658 (27.5)	20663.3 (6496.8, 39772.6)		
No	22845 (72.5)	11184.3 (4061.0, 29481.2)		
Length of stay			13688.72	< 0.001
≤ 7	12743 (40.5)	4164.3 (2437.0, 10429.7)		
7 ~ 14	8415 (26.7)	15525.2 (6665.8, 28756.5)		
15 ~ 28	7387 (23.4)	32913.6 (16951.3, 50388.7)		
≥ 28	2958 (9.4)	48881.1 (24547.5, 79274.4)		
Hospital level			-55.27	< 0.001
Grade 2	11410 (36.2)	6282.5 (3112.5, 19678.1)		
Grade 3	20093 (63.8)	20389.8 (6679.5, 39244.8)		
Payment mode			550.33	< 0.001
Medicare	10172 (32.3)	19916.9 (6335.2, 35641.2)		
Self-pay	18528 (58.8)	10154.6 (3970.9, 29969.7)		
Other	2803 (8.9)	15343.5 (5035.8, 33992.5)		

Notes: IQR, interquartile range. *P*-value testing difference between subgroups were compared by Mann–Whitney U-test or Kruskal–Wallis H-test, as appropriate.

Table 2
Association between the factors and the hospitalization costs of inpatients with TF in the QR model.

	QR (Ln (hospitalization costs))									
Variables	**Quantile 0.1**		**Quantile 0.3**		**Quantile 0.5**		**Quantile 0.7**		**Quantile 0.9**	
	β	***P*-value**	**β**	***P*-value**	**β**	***P*-value**	**β**	***P*-value**	**β**	***P*-value**
Gender (ref. male)										
Female	0.007	0.618	0.002	0.833	0.001	0.881	0.004	0.588	0.014	0.158
Age (in years)	0.004	< 0.001	0.005	< 0.001	0.005	< 0.001	0.004	< 0.001	0.003	< 0.001
Type of fracture (ref. 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
Other	0.560	< 0.001	0.478	< 0.001	0.419	< 0.001	0.357	< 0.001	0.352	< 0.001
Multiple fracture	0.506	< 0.001	0.455	< 0.001	0.369	< 0.001	0.284	< 0.001	0.271	< 0.001
Osteoporosis (ref. no)										
Yes	-0.037	0.237	-0.061	0.06	-0.080	< 0.001	-0.075	< 0.001	-0.108	< 0.001
Operation level (ref. without)										
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 (ref. no)										

Notes: Coefficients estimated after adjusting for all variables in the table. β, coefficient; ref, reference. .

	QR (Ln (hospitalization costs))									
Variables	**Quantile 0.1**		**Quantile 0.3**		**Quantile 0.5**		**Quantile 0.7**		**Quantile 0.9**	
	β	***P*-value**	**β**	***P*-value**	**β**	***P*-value**	**β**	***P*-value**	**β**	***P*-value**
Yes	0.107	< 0.001	0.108	< 0.001	0.097	< 0.001	0.087	< 0.001	0.074	< 0.001
Length of stay (ref. in days)	0.026	< 0.001	0.033	< 0.001	0.037	< 0.001	0.040	< 0.001	0.044	< 0.001
Hospital level (ref. 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 (ref. self-pay)										
Medicare	0.104	< 0.001	0.078	< 0.001	0.074	< 0.001	0.059	< 0.001	0.062	< 0.001
Other	-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: Coefficients estimated after adjusting for all variables in the table. β, coefficient; ref, reference. .										

Table 3 showed BPNN performance in predicting hospitalization costs. Predictions made by the model were satisfactory on hospitalization costs with R-squared values of 0.6556 and MSE values of 376.54 million. For the BPNN model, gradient of input represented their contributions to the output, serving as a promising indicator for feature importance on predicting. Figure 2 showed the importance of each feature to the hospitalization costs from the BPNN model. It can be seen that the length of stay, operation level and hospital level were identified as top 3 key drivers of hospitalization costs and the feature importance of them were 0.963, 0.886 and 0.447, respectively. The length of stay has the greatest impact on the total hospitalization cost and its various cost classifications.

Table 3
The performance of the ANN model.

	R^2	MAE	MSE (million)	RMSE
Training set	0.6638	10945	422.25	20548
Test set	0.6556	10621	376.54	19404

Notes: R2, R-squared; MAE, Mean Absolute Error; MSE, Mean Square Error; RMSE, Root Mean Square Error.

Discussion

In recent years, Zhuhai has implemented a series of medical reform policies to control medical costs and ensure proper medical services. In this investigation, we demonstrated that the median hospitalization cost of TF patients was ¥13528.2 and the mean length of stay was 13.77 days. We analyzed the factors influencing the hospitalization cost of TF patients by QR and Neural network modeling. The QR analysis showed that older age, more severe types of fractures, having operation, having comorbidity, longer length of stay, higher levels of hospital and payment with Medicare were significantly associated with higher hospitalization costs. Furthermore, machine learning algorithms demonstrated that the length of stay, operation level and hospital level were the most important predictors of hospitalization costs.

The finding that longer hospital stays were associated with higher hospitalization costs is consistent with previous studies[13, 22]. This suggests efforts to reduce the length of hospital stays may help to lower hospitalization costs for TF patients. For example, early rehabilitation may be an effective strategy to reduce the length of stays while improving patient outcomes. Our results also showed that advanced age was associated with higher hospitalization costs, which is consistent with previous studies[23–24]. A potential interpretation could be that older patients are more likely to have comorbidity and require more complex medical care[25]. In addition, our results indicated that more severe types of fractures were associated with higher hospitalization costs. This is also consistent with previous studies and highlights the importance of accurate diagnosis and appropriate treatment for different types of fractures[26]. Finally, higher level of hospital was associated with higher costs. The tertiary hospitals' hospitalization costs are higher than those in secondary hospitals because tertiary hospitals have better medical equipment, services, and higher treatment standards when compared to secondary hospitals. Therefore, the tertiary hospitals also receive patients with more complex and severe conditions, resulting in higher hospital costs and hospital days for tertiary hospital patients. Efforts to improve the efficiency and quality of medical care at lower level of hospital may help to reduce hospitalization costs for TF patients.

Our second finding demonstrated, with the neural network model, that the length of stay, operation level and hospital level were the most important predictors of hospitalization costs. Machine learning has also been successfully applied in orthopedics to predict costs in total hip and knee arthroplasty [27–28], total shoulder arthroplasty [29], and spinal fusion[30]. Karnuta *et al.*[31] created a machine learning algorithm that predicted total cost, discharge disposition, and length of stay following shoulder arthroplasty using the National Inpatient Sample. Our results indicated that the length of stay, operation level and hospital level were the most important predictors of hospitalization costs, suggesting that minimize hospitalization time while ensuring treatment effectiveness is an important means of reducing hospitalization costs. Besides, to strengthen the gatekeeping role of primary medical and health institutions, the patient's preoperative waiting and postoperative recovery into the primary hospital, is conducive to reduce the economic burden of patients.[8]

There are several limitations to this study. First, the data were obtained from a single site, which could potentially limit the generalizability of our findings to other populations or healthcare systems. Secondly, we only considered a limited set of predictor variables in our analysis based on research questions and data availability. It is not unlikely that some other variables contributing to hospitalization costs got excluded. Finally, with a specific focus on hospitalization costs, we did not consider other aspects of the economic burden of TF, such as indirect costs and lost productivity. Future studies could add more influencing factors to further verify the model and propose finer-grained and more specific measures to effectively control and reduce the hospitalization costs of TF patients.

In conclusion, our study offers insightful observations on the hospitalization costs of TF patients in China. The results showed that the length of stay, operation level and hospital level were the most important predictors of hospitalization costs. Our findings could be valuable for healthcare providers and policymakers in China who are interested in managing and reducing the hospitalization costs of TF patients. Future studies should investigate other factors that contribute to the costs of TF and explore strategies to reduce the economic burden of this important public health issue.

Abbreviations

TF: Traumatic fractures

QR: quantile regression

BPNN: Backpropagation neural network

Declarations

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Authors’ contributions

Peixin Liu: Conceptualization, Methodology, Software, Data curation, Writing - Original draft preparation; Zhongshu Ye: Data curation, Writing - Original draft preparation; Liqiang Zhou Visualization, Investigation; Xuyang Geng, Zefang Lin: Writing - Reviewing and Editing; Xiaodong Liu: Visualization, Investigation; Hong Jiang: Conceptualization, Methodology, Software, Validation; Yi Qin: Supervision.

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Availability of data and materials

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

Ethics approval and consent to participate

This study was approved by the Ethics Committee in Zhuhai People's Hospital, with informed consent from patient being waived (No.ZYEC (R)2023-034).

Consent for publication

Not applicable in the declarations section.

Competing interests

The authors declare that they have no competing interests.

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Figures

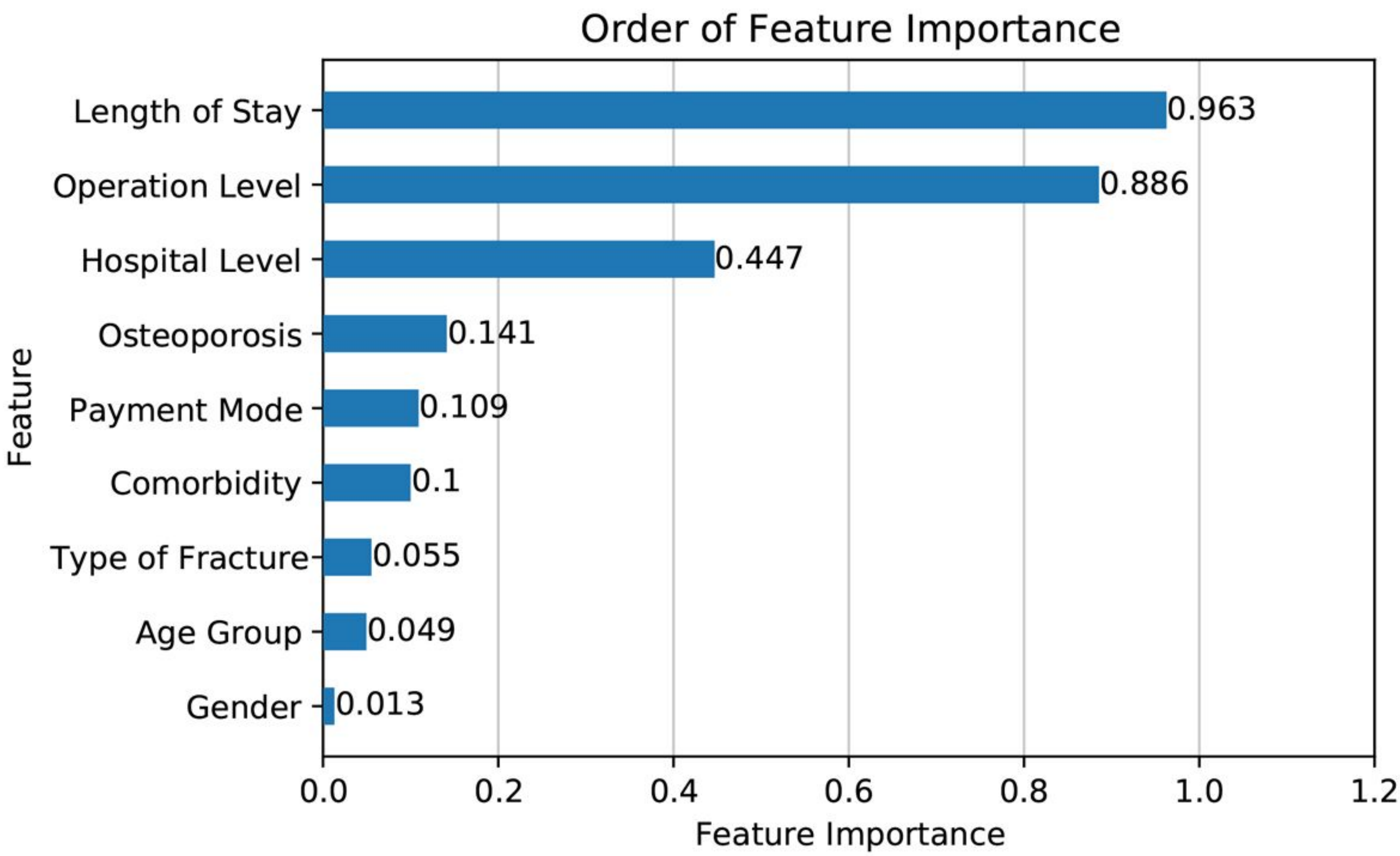
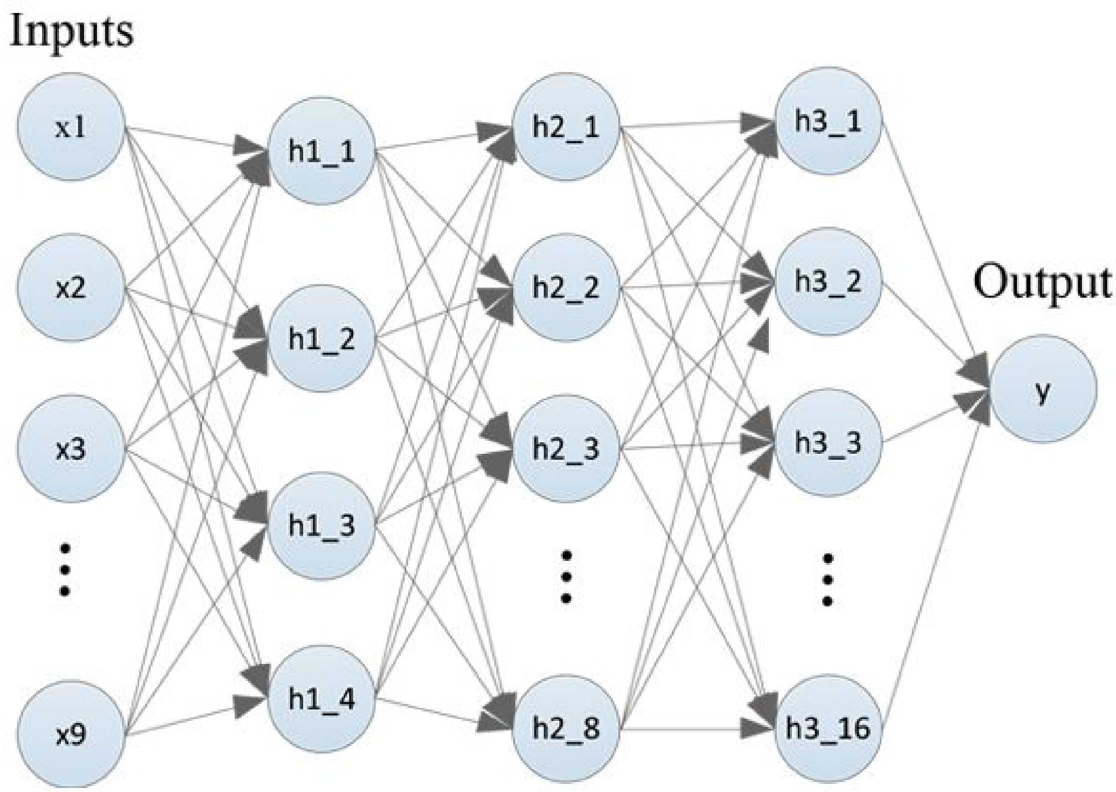

Order of Feature Importance
Length of Stay
Operation Level
Hospital Level
Osteoporosis
Payment Mode
Comorbidity
Type of Fracture
Age Group
Gender
0.963
0.886
0.447
0.141
0.109
0.1
0.055
0.049
0.013
Feature
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Feature Importance

Figure 0



Inputs
x1
x2
x3
x9
h1_1
h1_2
h1_3
h1_4
h2_1
h2_2
h2_3
h2_8
h3_1
h3_2
h3_3
h3_16
Output
y

Figure 1

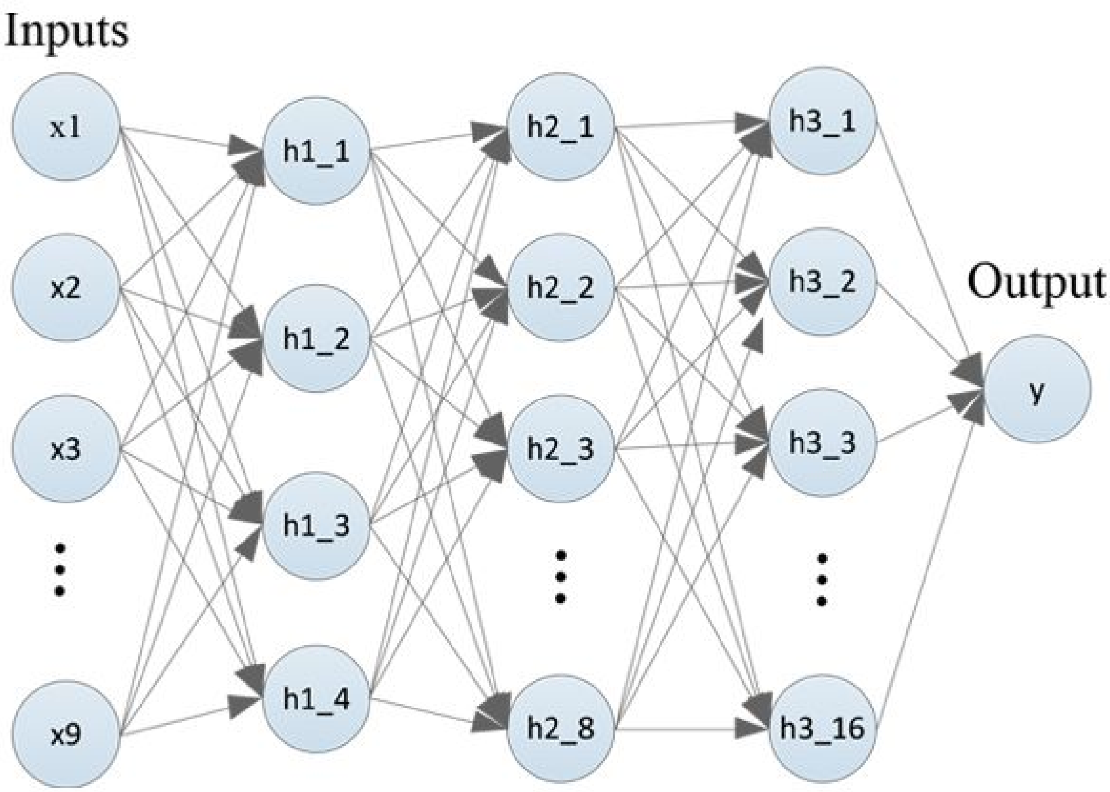


Figure 1

Structure of our BPNN model. Xs denoted the input features. Hs denoted neuron nodes inhidden layers. Ys denote the output, i.e. hospitalization cost.

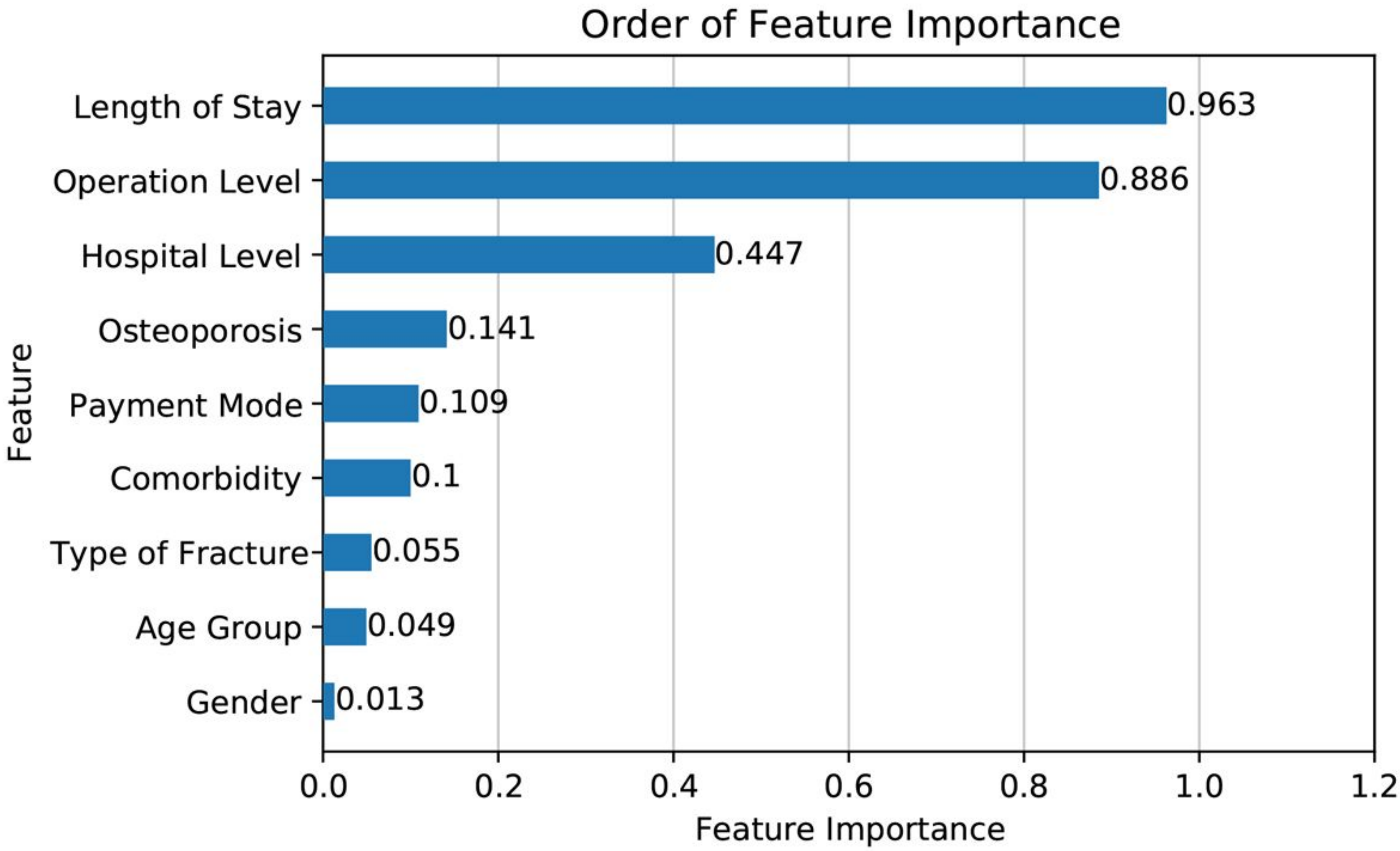


Figure 2

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