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ORIGINAL RESEARCH

Analysis of the Cost and Case-mix of Post-acute Stroke Patients in China Using Quantile Regression and the Decision-tree Models

Mengjia Zhi[1], Linlin Hu[1], Fangli Geng[2], Ningjun Shao[3], Yuanli Liu[1]

[1]School of Health Policy and Management, Chinese Academy of Medical Sciences & Peking Union Medical College, Beijing, 100710, People's Republic of China; [2]Ph.D. Program in Health Policy, Harvard University Graduate School of Arts and Sciences, Cambridge, MA, USA; [3]Jinhua Healthcare Security Administration, Zhejiang, 321000, People's Republic of China

Correspondence: Linlin Hu; Yuanli Liu, School of Health Policy and Management, Chinese Academy of Medical Sciences & Peking Union Medical College, Beijing, 100710, People's Republic of China, Tel/Fax +86 65105830, Email hulinlin@sph.pumc.edu.cn; Liuyuanli_pumc@163.com

Purpose: Post-acute care is fast developing in China, yet a payment system for post-acute care has not been established. As stroke is the leading cause of mortality and disability in China, patients constitute a large share of post-acute-care patients among all hospitalized patients. This study was to identify the cost determinants and establish a case-mix classification of the post-acute care system for stroke patients in China.

Patients and Methods: A total of 5401 post-acute stroke patients in seven hospitals of Jinhua City from January 2018 to December 2020 were selected. Demographic characteristics, medical status, functional measures (eg, the Barthel Index, Mini-Mental State Examination, Gugging Swallowing Screen, Hamilton Depression Scale), and cost data were extracted. Generalized linear model (GLM) and quantile regression (QR) were conducted to determine the predictors of cost, and a case-mix classification model was established using the decision-tree analysis.

Results: The GLM regression revealed that gender, tracheostomy, complication or comorbidity (CC), activities of daily living (ADL), and cognitive impairment were the main variables significantly affecting the hospitalization expenses of post-acute stroke patients. The QR model showed that the gender, tracheostomy and CC factors had a more significant impact on per diem costs on the upper quantiles. In contrast, cognitive impairment had a more substantial effect on the lower quantiles, and ADL significantly impacted the central quantile. Using tracheostomy, CC, and ADL as node variables of the regression tree, 12 classes were generated. The case-mix classification performed reliably and robustly, as measured by the reduction in the variation statistic (RIV=0.46) and class-specific coefficients of variation (CV less than 1.0; range: 0.18–0.81).

Conclusion: QR has strengths in comprehensively identifying cost predictors across cost groups. Tracheostomy, CC, and ADL significantly can predict the expenses of post-acute care for stroke patients. The established case-mix classification system can inform the future payment policy of post-acute care in China.

Keywords: cost, case-mix, post-acute care, stroke, quantile regression, decision-tree model

Introduction

Stroke has induced a heavy disease burden worldwide, especially in developing countries.[1] Annually, more than 1.9 million people die of stroke, making it the most significant cause of death in China.[2] Approximately 70% of stroke survivors are left with varying degrees of speech and physical dysfunction.[3] Moreover, stroke is an expensive disease to live with, as stroke care is a long-term process.[3] Not only are the expenses in the acute stage of stroke or surgical treatment high, but the long-term costs in the post-acute phase also bring a substantial economic burden to stroke patients, their families, and society.[4]

As far as recent reform, China's health insurance payment system is transforming from retrospective to prospective payment.[5] Although payment based on diagnosis-related groups (DRG) is utilized for acute care, the prospective payment

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method for China's post-acute service system has not been developed yet.[6] As delivered in many countries, post-acute care (PAC) is the kind of care aimed to assist recuperation of patients and facilitate independence or transition to continuing care in the community.[7] Case-mix is a tool to classify varieties of patient conditions based on resource utilization.[8] DRG, the case-mix that has been used as a payment system for acute inpatient services, has been piloted as a three-year project in 30 cities in China since 2019.[5] However, DRG for post-acute episodes are not well classified and it is widely accepted that post-acute care requires a different classification measure because various clinical issues, modes of care, and resource use are different from other types of health care.[9–12] Instead of being a short episode of care for an operation or acute treatment, post-acute services are time-consuming to maintain or improve the functional status of patients. Therefore, it is crucial to establish a reliable and well-validated case-mix classification system for post-acute care patients, especially those hospitalized for stroke in China, as the demand for post-acute care increases dramatically.

In China, a wealth of studies have spotlighted the costs of short-term hospitalization and early intensive care in the acute phase of stroke[3,13–15] under DRG payment policy,[4] however, there have been no previous studies exploring the case-mix of post-acute care. Several case-mix systems of post-acute care have been developed worldwide, among which the Resource Utilization Group Version III (RUG-III) is the most widely used.[16] RUG-III was a per diem classification system applied in the United States in 1994, which grouped patients into 44 classes and explained 55.5% of the variance in per diem costs, based on the clinical characteristics, special needs, and a nursing dependency level called the Resource Utilization Group-Activities of Daily Living (RUG-ADL) score.[17,18] A series of studies have been conducted to evaluate the effectiveness of RUG-III and have revealed various statistical performance levels, explaining 14.1% to 66.5% of the variance in per diem costs.[18–22] Even though those international studies have identified several functional and other measures as independent variables for PAC costs, it is vital to study whether the factors identified by international studies will be sound predictors for PAC costs in Chinese settings.

In addition, most studies have used linear regression models to examine predictors of costs.[23] However, the linear regression model cannot provide enough information about the underlying associations between costs and its predictors, as it focuses solely on the conditional mean of costs.[24] Furthermore, the linear regression model is not robust in the face of statistical outliers and lacks flexibility in analyzing the predictors of costs.[23] As cost data always have a skewed distribution, QR analysis is preferably employed because it allows for the study of individuals with extreme (low or high) costs.[25]

To address those gaps, our study established and validated the first case-mix classification that describes post-acute care for patients hospitalized for stroke. In addition, we investigated the determinants of the PAC costs for stroke through QR analysis. The study results can guide the payment policy for post-acute care in China.

Materials and Methods

Data Collection

In this study, seven hospitals, including three stand-alone rehabilitation hospitals and four rehabilitation units of acute care hospitals in Jinhua City, Zhejiang Province of southeast China, were selected. Post-acute stroke patients (patients with a primary stroke diagnosis and who were treated in rehabilitation or geriatric wards) hospitalized in the seven hospitals were selected from January 1, 2018 to December 31, 2020 with their medical records and functional assessment data extracted. The functional assessment data (BI, MMSE, HDS and GUSS) for each patient were routinely collected by medical staff in these hospitals at the point of admission. With the support of the local Healthcare Security Administration, medical insurance claims data for these patients on the medical cost they incurred were extracted. A flowchart showed the selection of study patients in Figure 1. Patients had to meet the following inclusion criteria to be eligible: with a primary diagnosis of stroke, treated in rehabilitation or geriatric wards, with complete medical cost data and functional assessment data (BI, MMSE, HDS and GUSS) at admission and no data quality issues, ≥18 years of age, alive at the point of discharge, with a length of stay more than three days. The exclusion criteria is: lack of stroke diagnosis, invalid or missing medical cost data or functional assessment data (BI, MMSE, HDS or GUSS) at admission, <18 years of age, with an outcome of death or a length of stay of fewer than three days. Finally, 5401 stroke PAC patients

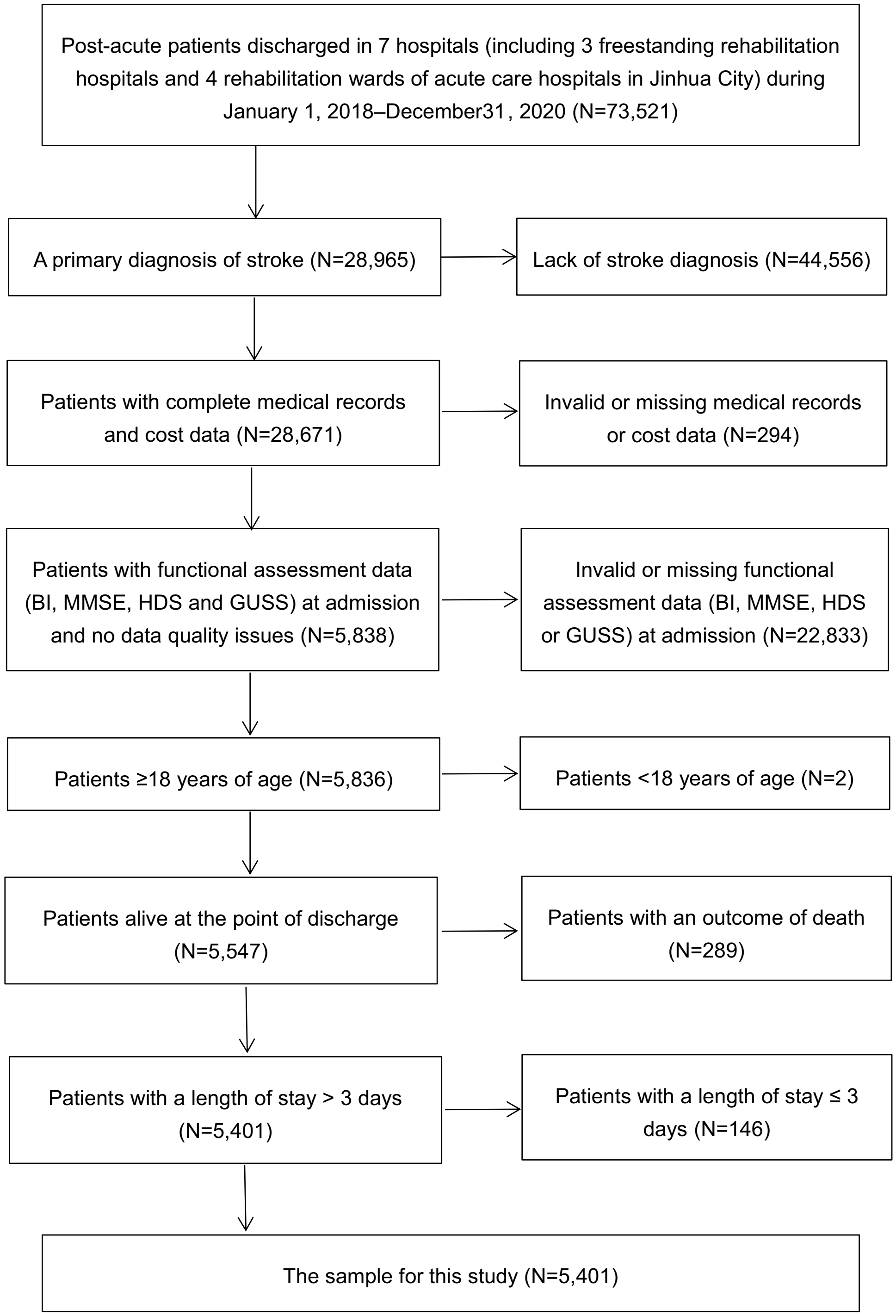

Figure 1 Selection of study patients.

were identified. Permission was obtained from the Medical Ethics Committee of the Chinese Academy of Medical Sciences & Peking Union Medical College to report the data for research purposes (Protocol number: X170315009).

Dependent Variable

The dependent variable was the resource use of the patients, which was measured by total expenses per day in the hospital in this study. Staff time is usually used to reflect resource use under RUG-III.[18] However, Acumen's report proposed that staff time should only be documented during the seven-day look-back window preceding each assessment.

The current data need not capture the exact number of minutes provided each day of a stay.[26] Moreover, costs should be considered to better reflect differences in the relative resource use across patients.[9,10] Therefore, in the present study, the measure of resource use was based on the costs during inpatient stays, which has been generally used in such studies in China.[3,15] The expenses included the costs of rehabilitation therapy, nursing, clinical treatment, medications and drugs, laboratory tests and examination, medical equipment and materials, room and board, and others. The Consumer Price Index (CPI) of Jinhua City, published by the National Bureau of Statistics of the People's Republic of China from 2018 to 2020 was used to revise all cost data and to compare cost data more scientifically. In addition, several studies have concluded that a per diem classification may be suitable for PAC, as the length of stay is not predictable[9,10,18] and the Social Security Act in the United States also requires payment be made on a per diem basis.[26] Thus, the dependent variable in the present study was the cost per day.

Independent Variables

There were three types of independent variables used to predict cost in this study: (1) patient demographic characteristics, including gender and age; (2) medical status measures: primary diagnosis (according to International Classification of Disease, 10th Edition, Clinical Modification codes), complication or comorbidity (CC), tracheostomy; (3) functional status data, including the Barthel Index (BI), Mini-mental State Examination (MMSE), Gugging Swallowing Screen (GUSS), and Hamilton Depression Scale (HDS). The following are explanations for some of the above measures.

Complication or Comorbidity

A complication refers to a medical condition directly caused by the principal diagnosis and has a causal relationship with the principal diagnosis; comorbidity refers to a medical condition that is not directly related to the principal diagnosis or complication, but has an impact on the resource consumption.[27] A major complication or comorbidity (MCC) has a greater impact on resource consumption compared with a complication or comorbidity (CC).[27] The official list of CCs and MCCs was published by the National Healthcare Security Administration of the People's Republic of China in October 2019.

Barthel Index (BI)

Activities of daily living (ADL) is measured by the BI, the most widely used physical function assessment instrument developed by Barthel.[28] It consists of 10 items: feeding, grooming, bathing, dressing, toilet use, transfers, walking, climbing stairs, bowel, and bladder control. The total score ranges from 0 (dependent) to 100 (independent). The present study calculated the ADL level using the following mapping: completely dependent (0–20), severely dependent (21–40), moderately dependent (41–60), and independent (61–100).[29]

Mini-mental State Examination (MMSE)

The MMSE is a widely used instrument designed to screen cognitive impairments, consisting of 30 items in seven domains, including orientation to time, orientation to place, registration, attention, calculation, spontaneous recall, language, and visual construction.[30] Scores less than 24 are typically suggestive of cognitive impairment, with the total score ranging from 0 (lowest) to a perfect score of 30 (highest).[31]

Gugging Swallowing Screen (GUSS)

The swallowing function was assessed by the GUSS, which is presented as a reliable and sensitive screening tool for testing conditions such as swallowing, coughing, drooling, and voice changes.[32] The present study considered scores less than 20 as a swallowing disorder, with the perfect score being 20.[33]

Hamilton Depression Scale (HDS)

The HDS is a measure of depressive symptoms that was developed by Hamilton and includes feelings such as guilt, suicide, sleep, work and interest, mental anxiety, somatic anxiety, gastrointestinal symptoms, weight loss, self-awareness, paranoid symptoms, obsessive–compulsive symptoms, feelings of hopelessness, and inferiority.[34] For the 17-item version, scores of HDS can range from 0 to 24, while scores between 18 and 24 indicate depressive symptoms.[35]

Statistical Analysis

We first conducted a descriptive analysis by calculating the costs on a per diem basis for post-acute stroke inpatients, followed by univariate analysis for patients with different demographic characteristics, clinical features, and functional statuses. We performed the Mann–Whitney *U*-test and the Kruskal–Wallis *H*-test to analyze the differences of the per diem costs among the patients with binary and multi-categorical characteristics. Only the characteristics that were found with a statistically significant difference in the costs of daily services were included in the multivariate analysis.

Two models, GLM and QR, were employed. As the cost data were not normally distributed, a generalized linear model (GLM) with a gamma distribution and log-link function was fit to model the regression. QR is a modeling technique that leads to more comprehensive results owing to its ability to assess the effect of each predictor on any part of the costs distribution, whereas a linear regression can model only the conditional mean of the costs.[24] To examine the effects of predictors at different points of the distribution of costs, this study used a QR model developed by Aheto.[25] The quantile plots of predictor effects on the quantiles of costs in the model permit visual examination of the predictor effects on each quantile.

The key influencing factors of the costs per day in the GLM and QR were taken as classification nodes, and the resource utilization classification model was established by using the growing method of the chi-squared automatic interaction detector (CHAID), and the standard costs per day were calculated.[25] The 10-fold cross-validation method was used to trim the decision-tree model automatically. The maximum tree depth was 3, the minimum number of cases in the parent node was 100, the minimum number of cases in the child node was 50, and the test level of the split node was $\alpha=0.05$. Overall performance of the classification was assessed with the reduction in variance (RIV), the Kruskal–Wallis test for intergroup heterogeneity, and the coefficient of variation (CV) for homogeneity of cases within each group. Relative weight (RW) was the ratio of resource use for each group to the mean cost for all patients. Statistical analyses were conducted with IBM SPSS version 26; the statistical significance level was $p<0.05$.

Results

For the 5401 patients, the average cost per day was 567.33±384.42 RMB (89.51±60.648 USD), and the average length of stay was 19.44 days (Table 1). More males (58.7%) than females (41.3%) were included in this study, with an average age of 66.96 years old for all patients. There were 195 (3.6%) stroke patients with tracheostomy for hospital care, 1893 (35.0%) with CC, 1802 (33.4%) with MCC, 564 (10.4%) who were moderately dependent on ADL, 1026 (19.0%) who were severely dependent on ADL, 334 (6.2%) who were completely dependent on ADL, 1699 (31.5%) who had cognitive impairment, 1536 (28.4%) who had swallowing disorder, and 137 (2.5%) who had depressive symptoms. The per diem cost of the PAC stroke inpatients with different demographic information, clinical characteristics, and

Table 1 Description of Cost and Length of Stay for PAC Stroke Inpatients (N=5401)

Variables	Mean	SD	P25	P50 (Median)	P75	Percent
Total cost of stay (RMB)	11,546.50	18,871.03	5193.75	7243.02	10,832.48	–
Length of stay (days)	19.44	20.47	12.00	15.00	22.00	–
Per diem Cost (RMB per day)	567.33	384.42	384.03	505.10	654.91	100.00
Therapy	241.01	185.88	156.09	226.00	313.34	42.48
Nursing	48.75	56.69	21.64	32.86	56.36	8.62
NTA	228.42	241.21	95.37	151.88	266.59	40.36
Routine	47.72	46.72	38.89	45.00	55.00	8.44

Notes: Therapy covers costs for physical therapy, occupational therapy, and speech-language pathology. Nursing covers costs for nursing. NTA covers costs for non-therapy ancillary services (eg, evaluation and drugs). Routine includes all other costs (eg, room and board).
Abbreviation: SD, standard deviation.

functional status are presented in Table 2. There were statistically significant differences (p<0.05) in the costs per day among the inpatients of a different gender, age, tracheostomy status, CC, ADL, cognitive impairment, swallowing disorder, and depressive symptoms.

Table 3 showed the result of GLM using log link and gamma distribution, three variables (ie, age, swallowing disorder, and depressive symptoms) were not statistically significant (p>0.05). After adjusting variables, five predictors (ie, gender, tracheostomy, CC, ADL, and cognitive impairment) were identified in the GLM regression (χ^2=4153.410, p=0.000) in Table 4. The positive coefficients of male (β=0.038, 95%CI: 0.021–0.055, p=0.000), tracheostomy (β=0.840, 95%CI: 0.792–0.888, p=0.000), CC (β=0.120, 95%CI: 0.099–0.141, p=0.000), MCC (β=0.302, 95%CI: 0.280–0.324, p=0.000), moderately dependent on ADL (β=0.147, 95%CI: 0.120–0.175, p=0.000), severely dependent on ADL (β=0.222, 95%CI: 0.200–0.244, p=0.000), totally dependent on ADL (β=0.306, 95%CI: 0.267–0.344, p=0.000), and cognitive impairment (β=0.138, 95%CI: 0.118–0.158, p=0.000) increased costs. The effect of tracheostomy on costs was

Table 2 Results of Univariate Analysis for PAC Stroke Inpatient Costs per Day (N=5401)

Variables	Frequency (%)	Mean (RMB per Day)	SD (RMB per Day)	Median (RMB per Day)	IQR (RMB per Day)	Z/H	p-value
Gender						−7.105	0.000**
Male	3173 (58.7)	593.94	456.816	525.35	294.96		
Female	2228 (41.3)	529.44	242.191	481.72	243.56		
Age (in years)						13.191	0.004**
<45	286 (5.3)	667.18	1169.109	530.66	230.63		
45–60	1384 (25.6)	565.62	298.909	504.86	270.85		
61–75	2217 (41.0)	564.55	264.810	517.76	266.59		
>75	1514 (28.0)	554.12	289.000	486.32	281.68		
Tracheostomy						−23.744	0.000**
No	5206 (96.4)	526.03	193.938	495.28	254.15		
Yes	195 (3.6)	1670.01	1355.135	1448.54	478.73		
CC						1103.881	0.000**
No	1706 (31.6)	453.62	492.096	401.00	186.88		
CC	1893 (35.0)	520.57	213.119	488.66	214.38		
MCC	1802 (33.4)	724.11	356.351	635.80	328.84		
ADL						959.169	0.000**
Independent (BI: 61–100)	3477 (64.4)	492.01	372.643	454.42	218.78		
Moderately dependent (BI: 41–60)	564 (10.4)	585.62	218.024	572.18	237.46		
Severely dependent (BI: 21–40)	1026 (19.0)	639.58	296.937	595.30	275.82		
Completely dependent (BI: 0–20)	334 (6.2)	1098.64	485.930	980.52	666.64		
Cognitive impairment						−31.927	0.000**
No (MMSE: 24–30)	3702 (68.5)	488.72	208.513	447.07	220.91		
Yes (MMSE: <24)	1699 (31.5)	738.62	576.519	636.41	288.11		
Swallowing disorder						−10.479	0.000**
No (GUSS=20)	3865 (71.6)	538.48	394.896	487.69	254.59		
Yes (GUSS <20)	1536 (28.4)	639.93	346.348	555.38	322.55		
Depressive symptoms						−2.270	0.023*
No (HDS: <18)	5264 (97.5)	566.89	387.546	503.82	270.15		
Yes (HDS: 18–24)	137 (2.5)	584.29	234.941	562.48	270.21		

Notes: Barthel ADL index (0–100): independent (BI: 61–100), moderately dependent (BI: 41–60), severely dependent (BI: 21–40), completely dependent (BI: 0–20); cognitive impairment (MMSE <24), swallowing disorder (GUSS <20), depressive symptoms (HDS: 18–24), *p<0.05, **p<0.01.

Abbreviations: SD, standard deviation; IQR, interquartile range; CC, complication or comorbidity; MCC, major complication or comorbidity; ADL, activities of daily living.

Table 3 Results I of Generalized Linear Model (GLM) Using Log Link and Gamma Distribution for PAC Stroke Inpatient Costs per Day (N=5401)

Variables	*β*	*SE*	95%CI		Wald χ^2	*p*-value	Likelihood Ratio χ^2	*p*-value
			Lower	Upper				
Intercept	6.009	0.0243	5.961	6.056	61,309.672	0.000*	4158.893	0.000*
Gender (ref. female)								
Male	0.038	0.0086	0.021	0.055	19.162	0.000*		
Age (in years)	−0.001	0.0003	−0.001	0.000	2.716	0.099		
Tracheostomy	0.836	0.0246	0.787	0.884	1150.490	0.000*		
CC (ref. no)								
CC	0.119	0.0107	0.098	0.140	124.949	0.000*		
MCC	0.300	0.0116	0.277	0.322	664.500	0.000*		
ADL (ref. independent)								
Moderately dependent	0.150	0.0143	0.122	0.178	110.074	0.000*		
Severely dependent	0.225	0.0112	0.203	0.247	401.840	0.000*		
Completely dependent	0.313	0.0202	0.274	0.353	239.427	0.000*		
Cognitive impairment	0.137	0.0104	0.117	0.158	175.796	0.000*		
Swallowing disorder	−0.007	0.0096	−0.026	0.012	0.521	0.471		
Depressive symptoms	0.042	0.0267	−0.010	0.095	2.514	0.113		
Scale	0.094	0.0018	0.091	0.098				

Notes: Cognitive impairment (MMSE <24), *$p<0.01$.
Abbreviations: *β*, coefficient; *SE*, standard error; 95%CI, 95% confidence interval; ref, reference; CC, complication or comorbidity; ADL, activities of daily living.

Table 4 Results II of Generalized Linear Model (GLM) Using Log Link and Gamma Distribution for PAC Stroke Inpatient Costs per Day (N=5401)

Variables	*β*	*SE*	95%CI		Wald χ^2	*p*-value	Likelihood Ratio χ^2	*p*-value
			Lower	Upper				
Intercept	5.972	0.0093	5.954	5.990	408,473.625	0.000*	4153.410	0.000*
Gender (ref. female)								
Male	0.038	0.0085	0.021	0.055	19.953	0.000*		
Tracheostomy	0.840	0.0245	0.792	0.888	1178.351	0.000*		
CC (ref. no)								
CC	0.120	0.0106	0.099	0.141	129.387	0.000*		
MCC	0.302	0.0114	0.280	0.324	704.140	0.000*		
ADL (ref. independent)								
Moderately Dependent	0.147	0.0142	0.120	0.175	107.558	0.000*		
Severely dependent	0.222	0.0110	0.200	0.244	404.116	0.000*		
Completely dependent	0.306	0.0198	0.267	0.344	238.452	0.000*		
Cognitive impairment	0.138	0.0103	0.118	0.158	178.398	0.000*		
Scale	0.094	0.0018	0.091	0.098				

Notes: Cognitive Impairment (MMSE<24), *$p<0.01$.
Abbreviations: *β*, coefficient; *SE*, standard error; 95%CI, 95% confidence interval; ref, reference; CC, complication or comorbidity; ADL, activities of daily living.

larger than the effect of other predictors. The assignment of variables are shown in Table 5, and the results of the GLM regression analysis are presented in Tables 3 and 4.

The QR results show significant differences among lower and upper quantiles in Table 6. The statistical significance between some variables (male, age, CC, moderately dependent on ADL, depressive symptoms) and per diem costs fluctuated across the seven quantiles, except for the swallowing disorder, which was not significant in costs per day across all quantiles. Moreover, predictors such as tracheostomy, MCC, ADL severely dependent, ADL completely dependent, and cognitive impairment increased per diem costs across all the quantiles. The effect of tracheostomy, CC, and MCC on per diem costs was more significant at the 95th quantiles than the effect at the lower quantiles. In contrast, the cognitive impairment effect on per day costs was more significant at the 5th quantile and smaller at the upper quantiles. ADL had a more significant effect on costs at the central quantile rather than the lower or upper quantiles. For instance, ADL severely dependent had a larger effect at the 90th quantile, while ADL moderately and completely dependent had a larger effect at the 75th quantiles. QR plots of slopes were developed to visually examine the impact of the predictors across selected quantiles (Figure 2).

Figure 3 shows the classification of the per diem costs for PAC stroke inpatients in China. Using classification and regression tree analysis, a regression tree was produced, in which PAC stoke patients were first split into two groups (tracheostomy and nontracheostomy). Second, patients without tracheostomy were subdivided into three groups by CC (without CC, with CC, and with MCC). Third, each branch was further classified by ADL, producing a classification with 12 classes. The “without CC” and “with MCC” branches were both split into four categories based on ADL, while the “with CC” branch was divided into three classes.

The RIV was as high as 0.46, reflecting a better grouping performance. Low CV (less than 1.0; range: 0.18–0.81) indicated slight variation and achieved better homogeneity within each group. The Kruskal–Wallis test was statistically significant (χ^2=2090.662, p=0.000), indicating that the intergroup heterogeneity was good and the classification was reasonable. The RW for individual classes ranged from 0.67 (class 2) to 2.94 (class 1). Higher RW reflected more costs or services provided to patients in that group. The median cost was used to determine the group’s payment standard. Each group’s upper limit was calculated as the 75th quantile plus 1.5 times interquartile range (P75+1.5IQR), which defined cases with excess cost.[6,36,37] After calculation, only 120 (2.22%) patients exceeded the upper limit of the cost control. Table 7 presents the statistical values of the per diem cost for all the groups.

Table 5 The Assignment of Independent Variables in the Regression Model

Variables		**Assignment**
Gender		Male=1, Female=0
Age (in years)		Original data
Tracheostomy		No=0, Yes=1
CC	No (X0) CC (X1) MCC (X2)	X1=0, X2=0 (reference) X1=1, X2=0 X1=0, X2=1
ADL	Independent (BI: 61–100) (X0) Moderately dependent (BI: 41–60) (X1) Severely dependent (BI: 21–40) (X2) Completely dependent (BI: 0–20) (X3)	X1=0, X2=0, X3=0 (reference) X1=1, X2=0, X3=0 X1=0, X2=1, X3=0 X1=0, X2=0, X3=1
Cognitive impairment		No (MMSE: 24–30)=0, Yes (MMSE <24)=1
Swallowing disorder		No (GUSS=20)=0, Yes (GUSS <20)=1
Depressive symptoms		No (HDS: <18)=0, Yes (HDS: 18–24)=1

Abbreviations: CC, complication or comorbidity; MCC, major complication or comorbidity; ADL, activities of daily living.

Table 6 Results of Multivariate Quantile Regression Analysis for Predictors of PAC Stroke Inpatient Costs per Day (N=5401)

Variables	**Quantiles**													
	q=0.05		**q=0.10**		**q=0.25**		**q=0.50**		**q=0.75**		**q=0.90**		**q=0.95**	
	β	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**	***β***	***p*-value**
Intercept	239.731	0.000**	298.596	0.000**	351.937	0.000**	346.725	0.000**	375.888	0.000**	443.560	0.000**	518.097	0.000**
Gender (ref. female)														
Male	11.135	0.084	0.290	0.959	−0.175	0.970	18.310	0.000**	34.545	0.000**	25.598	0.006**	29.606	0.040*
Age (in years)	−0.364	0.132	−0.492	0.021*	−0.483	0.006**	0.177	0.321	0.655	0.005**	1.018	0.004**	1.033	0.056
Tracheostomy	704.326	0.000**	686.904	0.000**	673.844	0.000**	690.934	0.000**	819.171	0.000**	1026.824	0.000**	1360.354	0.000**
CC (ref. no)														
CC	18.734	0.019*	8.899	0.207	23.629	0.000**	66.070	0.000**	92.447	0.000**	113.083	0.000**	122.215	0.000**
MCC	79.786	0.000**	85.092	0.000**	107.776	0.000**	159.488	0.000**	225.745	0.000**	283.053	0.000**	291.139	0.000**
ADL (ref. independent)														
Moderately dependent	7.081	0.507	14.101	0.134	59.524	0.000**	84.514	0.000**	128.320	0.000**	123.563	0.000**	113.759	0.000**
Severely dependent	55.744	0.000**	62.968	0.000**	81.553	0.000**	116.864	0.000**	168.758	0.000**	183.523	0.000**	162.405	0.000**
Completely dependent	117.333	0.000**	129.639	0.000**	188.760	0.000**	278.387	0.000**	330.307	0.000**	294.265	0.000**	246.646	0.000**
Cognitive impairment	99.438	0.000**	98.495	0.000**	91.960	0.000**	72.997	0.000**	41.898	0.000**	37.515	0.001**	46.151	0.008**
Swallowing disorder	0.474	0.948	−1.157	0.856	5.131	0.328	5.105	0.336	5.817	0.406	−15.318	0.143	−17.288	0.284
Depressive symptoms	47.596	0.017*	43.262	0.014*	16.735	0.250	20.476	0.165	15.429	0.427	36.830	0.205	28.891	0.519
Pseudo R^2	0.177		0.204		0.258		0.319		0.385		0.466		0.508	

Notes: Barthel ADL index (0–100): independent (BI: 61–100), moderately dependent (BI: 41–60), severely dependent (BI: 21–40), completely dependent (BI: 0–20); cognitive impairment (MMSE <24), swallowing disorder (GUSS <20), depressive symptoms (HDS: 18–24), *p<0.05, **p<0.01.
Abbreviations: q, quantile; β, coefficient; ref, reference; CC, complication or comorbidity; MCC, major complication or comorbidity; ADL, activities of daily living.

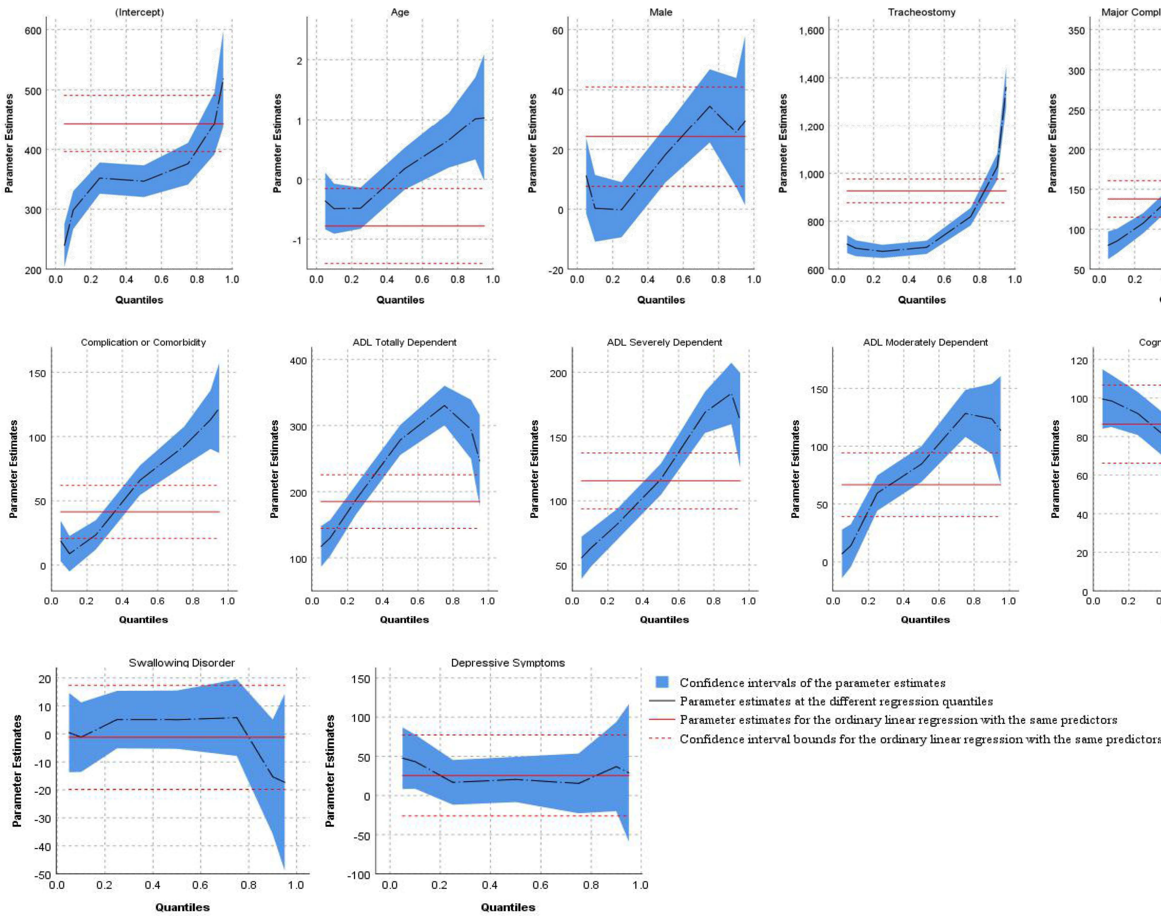

Figure 2 Quantile regression plot of predictors effect on quantiles of PAC stroke inpatient per diem costs distribution.

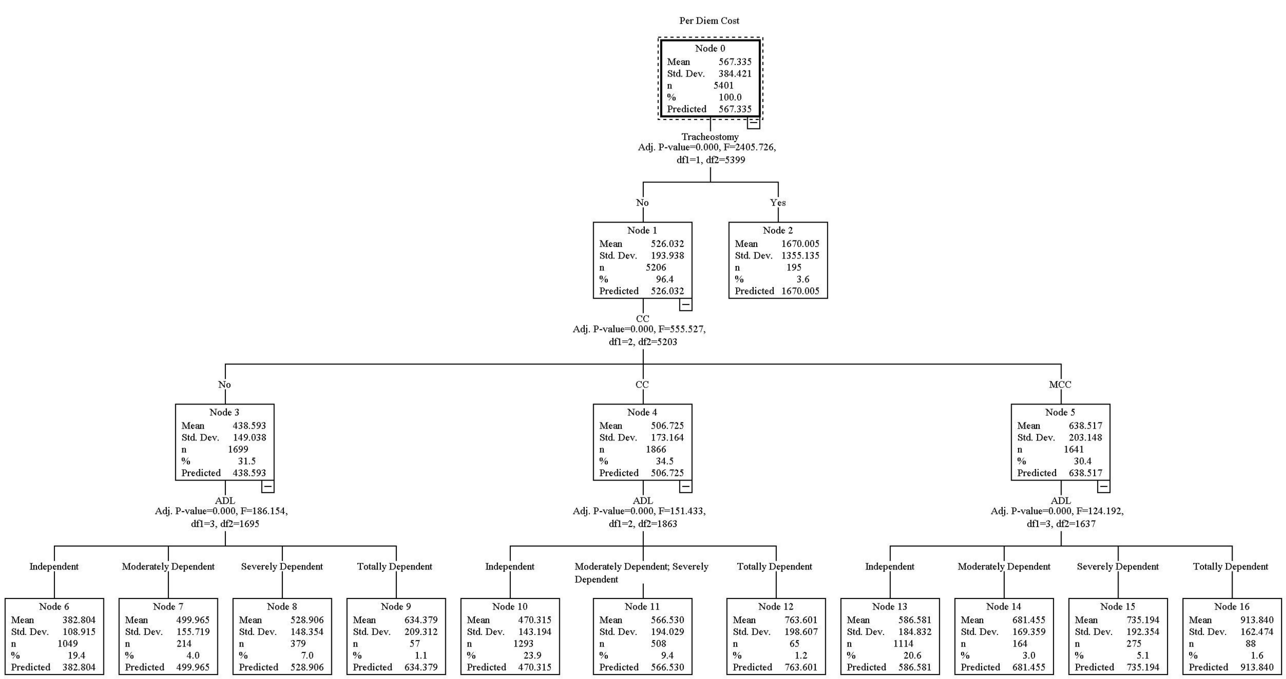

Figure 3 Classification of the per diem costs for PAC stroke inpatients in China (N=5401).

Notes: Barthel ADL index (0–100): independent (BI:61–100), moderately dependent (BI: 41–60), severely dependent (BI: 21–40), completely dependent (BI: 0–20).

Abbreviations: CC, complication or comorbidity; MCC, major complication or comorbidity; ADL, activities of daily living.

Table 7 The Case-mix Classification and the Standard Costs per Day of PAC Stroke Inpatients in China (RMB per Day)

Class	Description	Frequency (%)	Mean	SD	CV	RW	Payment Standard	P75	*IQR*	Upper Limit (P75 +1.5IQR)	Outlier (%)
Class 1	Tracheostomy	195 (3.61)	1670.01	1355.135	0.811	2.94	1448.54	1746.75	478.73	2464.85	10 (5.13)
Class 2	Without any CC, ADL independent	1049 (19.42)	382.80	108.915	0.285	0.67	363.36	428.82	108.82	592.05	52 (4.96)
Class 3	Without any CC, ADL moderately dependent	214 (3.96)	499.97	155.719	0.311	0.88	502.38	604.39	217.05	929.97	3 (1.40)
Class 4	Without any CC, ADL severely dependent	379 (7.02)	528.91	148.354	0.280	0.93	522.26	636.76	215.34	959.77	1 (0.26)
Class 5	Without any CC, ADL completely dependent	57 (1.06)	634.38	209.312	0.330	1.12	634.80	787.63	307.47	1248.84	1 (1.75)
Class 6	With CC, ADL independent	1293 (23.94)	470.31	143.194	0.304	0.83	460.23	551.99	177.74	818.60	23 (1.78)
Class 7	With CC, ADL moderately or severely dependent	508 (9.41)	566.53	194.029	0.342	1.00	547.02	691.15	271.74	1098.76	3 (0.59)
Class 8	With CC, ADL completely dependent	65 (1.20)	763.60	198.607	0.260	1.35	740.64	914.20	321.80	1396.90	0 (0.00)
Class 9	With MCC, ADL independent	1114 (20.63)	586.58	184.832	0.315	1.03	566.52	691.23	229.51	1035.50	25 (2.24)
Class 10	With MCC, ADL moderately dependent	164 (3.04)	681.45	169.359	0.249	1.20	660.05	777.67	214.75	1099.80	2 (1.22)
Class 11	With MCC, ADL severely dependent	275 (5.09)	735.19	192.354	0.262	1.30	720.22	884.25	291.61	1321.67	0 (0.00)
Class 12	With MCC, ADL completely dependent	88 (1.63)	913.84	162.474	0.178	1.61	926.91	1058.41	263.20	1453.21	0 (0.00)

Notes: Barthel ADL index (0–100): independent (BI: 61–100), moderately dependent (BI: 41–60), severely dependent (BI: 21–40), completely dependent (BI: 0–20).
Abbreviations: SD, standard deviation; CV, coefficient of variation; RW, relative weight; IQR, interquartile range; CC, complication or comorbidity; MCC, major complication or comorbidity; ADL, activities of daily living.

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Discussion

Our study was the first to develop a case-mix classification of post-acute care for stroke patients in China. An important feature of our study was that we included several functional measures in predicting resource use, which was found to be relevant in other research.[4,10,16] For the classification methodology, the key determinants (tracheostomy, CC, ADL, and cognitive impairment) were identified by QR and linear regression. Then the CHAID decision-tree analysis was conducted to provide statistics for classification. To date, this remains the only comprehensive QR study modeling the costs of PAC stroke patients in China. The following are the key points of discussion.

Four main variables, tracheostomy, CC, ADL, and cognitive impairment, were identified as the primary predictors of the per diem costs for PAC stroke inpatients in China. For tracheostomy, Acumen reported that tracheostomy was considered one of the best cost predictors for PAC because it is often performed in critically ill stroke patients who require intensive care and medical treatment.,26,[4,10,16],26 Ikegami et al also proposed a high correlation between tracheostomy and the per diem cost.[19] Similar to our findings, the cost of the tracheostomy group was significantly higher than that of the nontracheostomy groups, so its influence on the overall hospitalization cost cannot be ignored. For CC, Matizirofa et al proposed that CC contributed a larger proportion to total costs for stroke patients in South Africa.[23] Khiaocharoen et al posited a strong relationship between CC and costs per day.[10] Our results are similar; CCs such as hypertension, diabetes, and heart problems were the primary drivers of the medical costs for stroke patients. For physical function status, a study conducted by Williams et al proposed functionality, as measured by ADL, was the most important predictor of the cost, explaining 30% of the variance in total cost.[38] Fries et al reported that ADL explained resource use well while ignoring most of the relatively rare heavy care patients.[17] Similarly, it is generally believed that function limitation or disability on ADL will lead to more resource consumption owing to the high demand for living care, skin care, and rehabilitation training. Cognitive function also significantly affects cost. Eilertsen et al reported that cognitive impairment was associated with slightly higher resource use for residents without major medical problems and serious functional dependencies.[7] Stineman et al considered that cognitive impairment was an important contributor to per diem cost.[8] Similar to our findings, patients with cognitive impairment, most of whom have communication difficulty and poor compliance, require additional care and increase the cost burden. This study demonstrated that it is necessary to include function variables as cost determinants in classifying the cost of post-acute patients.

As to the QR model, traditionally, linear regression was used to identify predictors of medical cost, yet modeling with QR could be more appropriate in our settings. As shown in Figure 1, linear regression solely focuses on the mean missed critical information of the underlying relationship that might exist between the cost conditional distribution and its predictors, especially in the presence of skewed data. This is because the conditional distribution of costs not only differed by their means, but also by their lower and upper tails.[23–25] Compared with linear regression, QR provided flexibility to analyze the cost predictors corresponding to quantiles of interest and was more robust to statistical outliers.[23]

The statistical performance of the case-mix classification system was favorable, with only 12 groups and an RIV of 0.46 for 5401 inpatients compared to other related case-mix classifications. Eilertsen et al conducted a classification for 290 stroke patients in rehabilitation facilities and 193 stroke patients in skilled nursing facilities (five groups, RIV=0.28).[7] In contrast, a modified classification explained more variance in resource use (five groups, RIV=0.41).[7] Furthermore, the RIV in the present study was better than that of the current Australian Aged Care Funding Instrument (ACFI) (64 groups, RIV=0.20),[39] but lower than the RIV of the Australian National Aged Care Classification (AN-ACC) (13 groups, RIV=0.52)[16] for 1877 aged care residents, as well the RUG-IV system used in the US (66 groups, RIV=0.62).[18] A recent overview of international validation studies of the RUG-III case-mix system in eight countries and regions revealed an RIV value between 0.14 and 0.67 (22–53 groups),[18] compared to which our results are also acceptable As a final point, setting the payment standards and upper limit for each group in Table 7 can help strengthen the management of cases with excess costs, effectively reducing the waste of resources and promoting equity and efficiency among payers, providers, and patients.

Limitations

Our study also has several limitations. First, this analysis was based on data drawn from seven hospitals in Jinhua City, further studies are needed when generalizing the results to the entire country. Second, as there are currently no uniform and mandate assessment instruments used in PAC settings in China, each institute uses a different set of assessment tools to measure patient severity and functional impairment levels. The function data in this study were collected by several assessment scales (BI, MMSE, GUSS, and HDS), but the assessments were not standardized across facilities. Therefore, it is necessary to develop standardized assessment tools for PAC settings in China and improve the quality of cross-setting data collection.

Conclusions

Identifying and quantifying cost drivers through QR models can benefit the cost study of post-acute care. We proposed a novel case-mix system closely classifying the level of resource use of post-acute stroke inpatients. The information generated from this study will be useful to facilitate the development of an appropriate payment method for post-acute-care patients in China. Due to the differences in payment and service systems across China, this case-mix also needs to be adjusted if promoted. In future research, studies should investigate the case-mix system for other diseases in Chinese PAC settings.

Ethics Approval

The facilities gathered the data routinely in clinical practice according to the requirement of the local Healthcare Security Administration. Permission has been obtained from the Medical Ethics Committee of the Chinese Academy of Medical Sciences & Peking Union Medical College to report the data for research purposes (Protocol number: X170315009). All the inpatients were informed about the study. Only the consenting patients were included, which secured a paper-written patient consent process. Such patient consent approach was approved by the Ethics Committee. As for the critically ill patients, their family members made the informed consent process and responded on their behalf. This study was conducted in accordance with the Declaration of Helsinki.

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Disclosure

The authors report no conflicts of interest in this work.

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