Forecasting Single Disease Cost of Cataract Based on Multivariable Regression Analysis and Backpropagation Neural Network

Fang Qing, PhD[1] and Chuang Liu, ME[1,2] iD

Abstract

In medical services, charge according to the disease is an important way to promote the reform of pricing mechanism, control the unreasonable growth of medical expenses, as well as reduce the burden on patients. Single disease cost forecasting that both identify potential influencing or driving factors and enable better proactive estimation of costs can guide the management and control of medical costs. This study aimed to identify the factors that affect the medical costs of single disease cataract and compare 2 regression models for anticipating acceptable medical cost forecasts. For this purpose, 483 patients with cataract surgery completed in West China Hospital from May 1, 2015, to October 1, 2015, were selected from hospital information system. For cost forecasting, multivariable regression analysis (MRA) and backpropagation neural network (BPNN) were used. Analysis of data was performed with SPSS21.0 and MATLAB2014a software. Total medical costs of patients with cataract (n = 483) ranged from 2015.00 to 13 359.00 CNY, and the mean $\pm$ standard deviation is 6292.29 $\pm$ 2639.43 CNY. Factors influencing costs of cataract in the MRA include, in importance order, intraocular lens (IOL) implantation ($|r|$: 0.805, $P < .01$), doctor level ($|r|$: 0.644, $P < .01$), payment source ($|r|$: 0.554, $P < .01$), admission status ($|r|$: 0.326, $P < .01$), additional diagnosis ($|r|$: 0.260, $P < .01$), type of surgery ($|r|$: 0.127, $P < .05$), and type of anesthesia ($|r|$: 0.126, $P < .05$). In terms of forecasting performance, BPNN (average error: 2.81%) outperforms, yet is less interpretable than MRA (average error: 5.79%). Both MRA and BPNN are technically and economically feasible in generating medical costs of cataract. And some insights on using results of the forecasting model in controlling and reducing disease costs are obtained.

Keywords

single disease cost, cost forecasting, cataract, regression analysis, backpropagation neural network

---

What do we already know about this topic?
Cost forecasting has been applied by many researches in various industries such as construction project, freight transportation, manufacturing, energy, with statistics, and machine learning methods such as linear regression, gray prediction, multivariable regression, multivariate time series, and backpropagation neural network (BPNN) applied.

How does your research contribute to the field?
Compared with plentiful researches on cost forecasting in industries such as construction, transportation, and manufacturing, cost forecasting in health care is mainly on identifying potential high-cost patients, forecasting total health care costs, evaluating expected population costs for contract pricing and premium setting, and individualized assessment of cost impacts of predictors, when it comes to single disease cost, there is little analysis on exploring its influencing factors specifically and exclusively.

What are your research's implications toward theory, practice, or policy?
With reasonable forecasting followed by management insights regarding patients and hospitals, it can help strengthen medical cost control, reduce medical expenses, and provide reference values for medical service pricing under the mode of charge according to the disease.

Introduction

To control the growing medical expenses, many countries have taken corresponding measures, among which "diagnosis-related groups (DRGs)," first adopted by the United States, is one of the most advanced payment methods throughout the world. Nowadays, remarkable success has been achieved in many other countries by introducing and revising this method in accordance with their national conditions, such as Australia national DRGs and refined DRGs (AN-DRGs and AR-DRGs),[1] Germany DRGs (G-DRGs),[2-4] Canadian case mix groups (CMGs),[5] and Japanese diagnosis procedure combination (DPC),[6] making the mode of charge according to the disease increasingly prominent. In line with this, China has been dedicated to the reform of medical insurance payment methods as well. Since 2017, China has been fully promoting the policy of multiple payment methods, among which, charge according to the disease (or single disease payment strategy) is primary and dominant. Under this mode, the paying party of medical insurance does not pay for the actual expenses of the inpatient, but pays according to DRGs. Therefore, in the case where the price of each disease has been predetermined, the hospital will not be able to increase charges by providing additional services or increasing the amount of services, making contribution to effectively regulating the charges in medical service industry, and reducing inductive medical expenses. As a result, it can bring down the medical expenses of patients without their suffering lower medical service level provided by the hospital, and meanwhile reduce the expenditure of medical insurance funds, as well as solve some disputes caused by high price within doctors, patients, and insurers.

This medical reform in China not only brings new challenges for hospital cost management but also makes it increasingly important. On one hand, cost factor should be taken into account when reforming payment system. The fact is that accurate medical services costing is an important work in the medical insurance reimbursement, and it raises higher requirements for medical service organizations to establish a scientific and rational cost management system. On the other, to adapt to changes in payment methods and achieve benign development, it is urgent for hospitals to not only strengthen cost forecasting and controlling but also seek a balance between medical cost controlling and the quality of medical services. Cost forecasting, as the basis of cost control,[7] is of potential to bring down medical costs by revealing and controlling its influencing factors. In addition, by comparing forecasts and actual cost values, gaps and causes can be identified, thus timely targeted measures can be taken to control medical costs. For this situation, most importantly, it helps to make people working in hospital pay more attention to economic benefits, establish awareness of frugality, and reduce medical costs in the end. Moreover, scientific cost forecasting can provide managers with information to judge the trend of future costs, prevent out-of-control phenomenon in cost management, and provide reference values for managers to make decisions, so as to minimize the blindness of decision-making.[7] However, due to the complexity and uncertainty of the costs of the disease, accurate forecasting is still an important and essential issue.

We piloted this study on cataract in ophthalmology department in West China Hospital (WCH) as both suggested by hospital managers and demonstrated by literatures for increasing patients in China tend to uptake surgeries in recent years as well as their first concern on costs.[8-10] Cataract, as the leading cause of treatable blindness in the world, is unbalanced distributed between developed and developing countries. Among all the blind in developed countries, only 5% are caused by cataract, while the figure surpasses 50% in developing countries.[11] Furthermore, with continuous population growth and accelerated aging of the society, it will become increasingly serious.[12,13]

Therefore, this article focuses on the mode of charge according to the disease and explores medical cost forecasting and control on cataract. To have the largest possible control over cataract costs, it is necessary to know both what factors are likely to influence the costs significantly and how to anticipate acceptable accurate forecasts which further guide the practice of cost control in return. It is of important practical significance for optimizing medical costs and expenses, solving the problem of reasonable pricing mechanism on medical services, in addition to effectively alleviating the pressure of growing medical expenses.

Literature Review

Cost forecasting has been applied by many researches in various industries, such as construction project,[14-17] freight transportation,[18] manufacturing,[19] and energy,[20] with statistics and machine learning methods such as linear regression, gray prediction, multivariable regression, multivariate time series, and backpropagation neural network (BPNN) applied.

[1]Business School, Sichuan University, Chengdu, China
[2]Logistics Engineering School, Chengdu Vocational & Technical College of Industry, China

Corresponding Author:
Chuang Liu, Logistics Engineering School, Chengdu Vocational & Technical College of Industry, No. 818 Da'an Road, Zhengxing New District, Chengdu 610218, Sichuan, China.
Email: liuchuangcd@163.com

Sun[18] analyzed the composition and influencing factors of the railway freight transportation cost in China and presented a hybrid model of activity-based costing and BPNN for forecasting the cost. Alshamrani[15] proposed a multivariable regression model for forecasting the construction cost of college buildings in North America. Wang[21] combined particle swarm optimization algorithm and BPNN for forecasting the cost of plastic injection molded parts. It can be concluded that multivariable regression is commonly used, while BPNN is receiving concern and development.

Compared with plentiful researches on cost forecasting in industries like construction, transportation, manufacturing, and so on, cost forecasting in health care is mainly on identifying potential high-cost patients,[22-24] forecasting total health care costs,[25-27] evaluating expected population costs for contract pricing and premium setting,[28] and individualized assessment on cost impacts of predictors.[29] When it comes to single disease cost, there is little analysis on exploring its influencing factors specifically and exclusively. However, regarding total costs, Wrathall and Belnap[30] demonstrated superiority of logistic regression over Classification and Regression Tree and Random Forest in identifying patients with higher medical costs and more comorbid conditions, while Lin et al[24] used Bayesian Network Frame for identifying high-cost chronic obstructive pulmonary disease patients as well as considering data sparsity. Munoz-Price et al[31] used the hospital utilization factor model to predict the relationship between hospital utilization and cost for the medical expenses of 70 patients in the long-term acute care hospital in Chicago. Zupancic et al[32] analyzed the National Health Insurance System implemented in Taiwan and worked out the influencing factors of medical costs by using panel data. Swierkowski and Barnett[33] used principal component analysis and LASSO (least absolute shrinkage and selection operator) to identify general cost drivers in a typical, mid-sized Australian hospital, including 32 potential cost predictors with a sample size of over 50 000 hospital admissions. Popesko et al[34] proposed that while there are different levels of cost system design, it seems remarkable that the number of hospitals analyzing and forecasting costs on a more detailed basis remains limited. Relative to other industries, the health care sector still lags behind. Existing studies make a basic contribution in either qualitatively analyzing the driving factors of single disease cost or forecasting for parts of medical costs like hospitalization,[35] high-cost patients.[23,24] However, due to the complexity of both the variable composition and the cost accounting for different diseases, plenty of influencing factors and existence of nonlinear relationship makes it a challenge to forecast accurately, hence focusing on disease itself makes sense. As a multilayer forward neural network, BPNN is mainly for prediction, classification, data compression, and function approximation and has been successfully applied in many fields. Considering the excellence of BPNN in both complex nonlinear mapping and generalization, we will construct a BPNN model to forecast single disease cost particularly based on analyzing its influencing factors particularly and demonstrate its advantage over multivariable regression analysis (MRA) in single disease forecasting.

Method

Multivariable Regression Analysis

Continuous development and improvement have made the theory of MRA relatively mature. It can find out the quantitative relationship between variables, describe the law of numerical variation between statistical variables, and finally carry out corresponding forecasting. Furthermore, it provides an effective way to accurately learn the influence degree and direction of independent variables on dependent variables. Multivariable regression analysis, including methods like linear regression, nonlinear regression, curve regression, logistic regression, and so on, has been applied widely in economics, medicine, finance, and social sciences. Given that the dependent variable is y, and the independent variables are $x_1, x_2, \ldots, x_k$, the multivariable linear regression equation describes how the dependent variable y depends on the independent variables and the error value ε. The equation can be written as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon,$$

where β_0 is regression constant, $\beta_1, \beta_2, \ldots, \beta_k$ are regression coefficients, and ε is an error term.

General MRA methodology consists of the following 5 steps. First, select the corresponding indicator variables according to the goal of the research. Second, collect and preprocess primary data. Third, conduct correlation analysis of candidate influencing factors with the outcome variable, that is, confounders selecting, commonly used statistical methods includes Pearson correlation coefficient, Spearman rank correlation coefficient, Kendall rank correlation, or partial correlation. Fourth, use adjusted R^2, Durbin–Watson and variance inflation factor (VIF) to test goodness of fit, series autocorrelation, and multicollinearity, respectively; meanwhile, estimates of parameters of multivariable regression models are obtained. At last, test both goodness of fit and parameters for the worked-out multivariable regression models by residual analysis.

Backpropagation Neural Network

Backpropagation neural network is a typical multilayer forward neural network using a tutor learning algorithm. The BPNN has an input layer, 1 or multiple hidden layers, and an output layer. Each layer is fully connected, but no interconnection between neurons in the same layer. Backpropagation is shorthand for "the backward propagation of errors," as an error is computed at the output and distributed backward
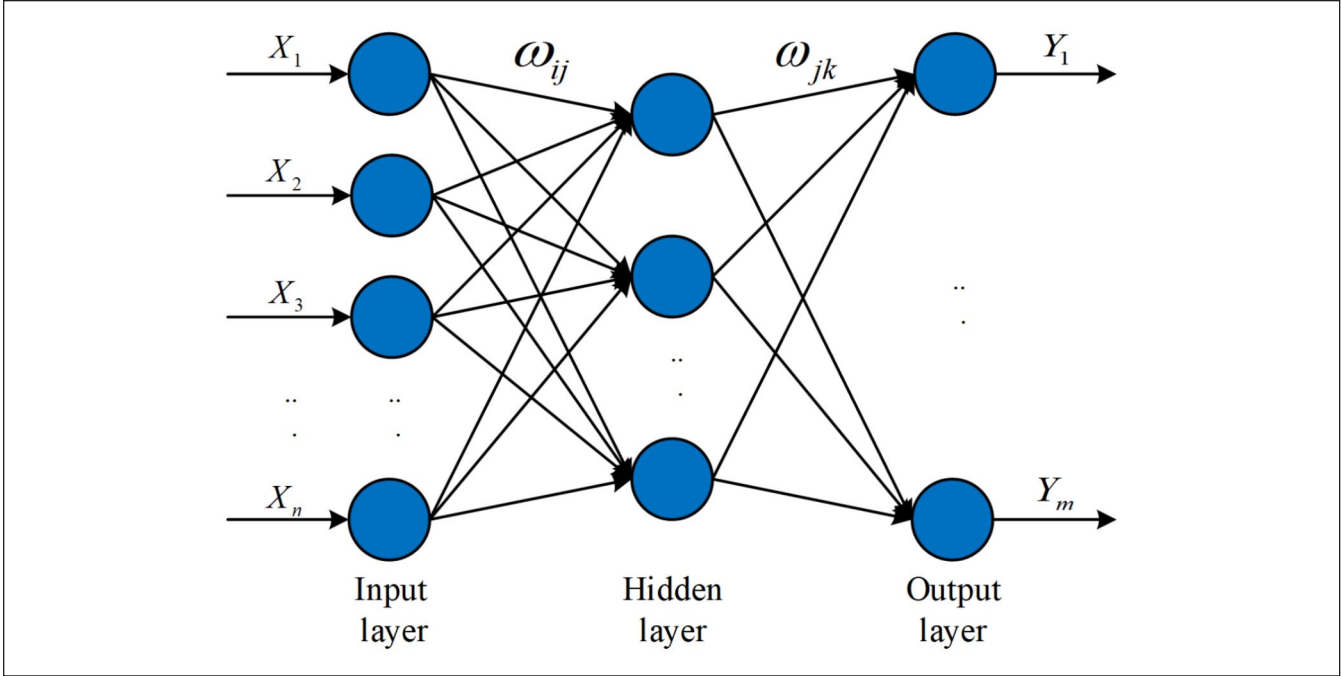
Figure 1. Backpropagation neural network topology.

throughout the network's layers. In the forward transmission process, the input signal is processed orderly from the input layer to the output layer, and the neuron of each layer only affects those in the next layer. If the output layer does not get the expected output, it will enter the backpropagation and adjust the weight and threshold of the neural network according to the prediction error, so that the predicted output of the BPNN is continuously approaching the expected output. In the BPNN, the neurons in the hidden layer generally adopt the S-type transfer function, and the neurons in the output layer mostly adopt the linear transfer function. Figure 1 shows a typical topology of a BPNN with a 3-layer network.

In Figure 1, the number of input nodes and output nodes are n and m, respectively. Accordingly, in the BPNN, $X_1, X_2, \ldots, X_n$ are input values, $Y_1, Y_2, \ldots, Y_m$ are forecasts, and ω_{ij} and ω_{jk} are weights.

The basic idea of BPNN is to learn a certain number of sample pairs (input and expected output). Specifically, the input data of the sample are sent to each neuron in the input layer, and after being calculated by the hidden layer and the output layer, each neuron of the output layer works out a corresponding forecast. Backpropagation neural network needs to train the sample data before forecasting, and the network acquires associative memory and forecasting ability via training. The training process in BPNN illustrated in Figure 2 includes following steps:

1. Network initialization

According to the system input and output sequence (X, Y), the number of neurons in single input, hidden, and output layer initialize the connection weights ω_{ij} and ω_{jk} between the input layer and the hidden layer, and the hidden layer and the output layer, respectively, as well as thresholds a and b in hidden and output layer, respectively. Accordingly, the learning rate and neuron excitation function can also be obtained.

2. Hidden layer output calculation

The hidden layer output R is calculated based on the input vector **X**, the connection weight ω_{ij} between the input layer and the output layer, and the hidden layer threshold a:

$$R_j = f\left(\sum_{i=1}^{n} \omega_{ij} x_i - a_j \right) j = 1, 2, \ldots, l,$$

where l is the number of neurons in hidden layer, and f is excitation function of the hidden layer, $f(x) = 1/(1+e^{-x})$.

3. Output layer output calculation.

The predicted output G of the BPNN is calculated based on the hidden layer output R, the connection weight ω_{jk}, and the output layer threshold b:

$$G_k = \sum_{j=1}^{l} R_j \omega_{jk} - b_k \quad k = 1, 2, \ldots, m.$$

4. Error calculation

Calculate prediction error e, which is the difference between the network prediction output G and the expected output Y:
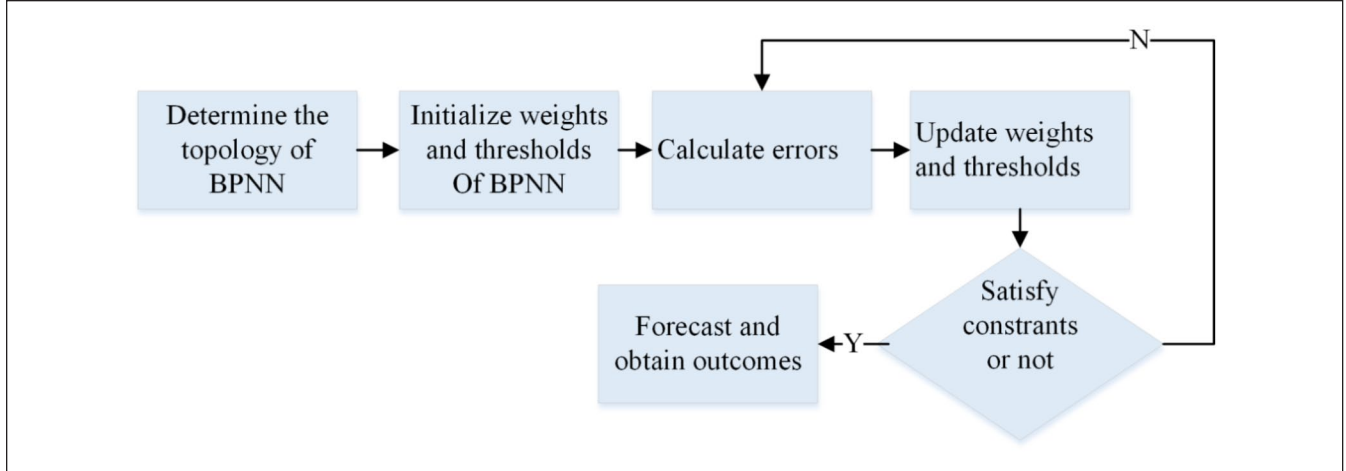
Figure 2. Backpropagation neural network (BPNN) flow chart.[18]

$$e_k = Y_k - G_k \ k = 1, 2, \ldots, m.$$

5. Weight updation

Update the network connection weights ω_{ij} and ω_{jk} according to the network prediction error e:

$$\omega_{ij} = \omega_{ij} + \eta R_j \left(1 - R_j\right) x(i) \sum_{k=1}^{m} \omega_{jk} e_k$$

$$i = 1, 2, \ldots, n; \ j = 1, 2, \ldots, l;$$

$$\omega_{jk} = \omega_{jk} + \eta R_j e_k \ j = 1, 2, \ldots, l; k = 1, 2, \ldots, m.$$

where η is the learning rate.

6. Threshold updation

Updating the network threshold, a and b according to the network prediction error e:

$$a_j = a_j + \eta R_j \left(1 - R_j\right) \sum_{k=1}^{m} \omega_{jk} e_k \ j = 1, 2, \ldots, l;$$

$$b_k = b_k + e_k \ k = 1, 2, \ldots, m.$$

7. Determination

Determine whether the algorithm iteration ends. If not, return to the second step and iterate, until the error is less than the set value.

Variables

Under the mode of DRGs, our primary outcome was the medical cost of one single disease, that is, cataract. And according to suggestions from 2 surgeons in the department of ophthalmology, patients with 2-eye cataract were excluded in our study to avoid cost bias. Then, we established 4 categories of predictor variables in the study based on the available data: (1) biological characteristics, (2) economic conditions, (3) pathological characteristics, and (4) medical institutions. Detailed information and all candidate variables can be referred in Table 2. Among which, categories 1 to 3 are related to patients' own, while category 4 is in relation with the hospital.

Data Exploration

This study was motivated by previously acquired data in ophthalmology department in a cooperation hospital as well as a typical hospital in China, that is, WCH. As an urban and public tertiary teaching hospital in Chengdu, WCH operates a large inpatient department that has a capacity of about 4300 licensed beds shared by 44 specialty care units or clinical departments as of December 31, 2018. At present, each unit or department operates cost accounting separately, and the total costs of each unit or department is divided into variable costs (sanitary materials, disinfection, washing, maintenance materials, etc), fixed costs (wages and welfare fees, depreciation of fixed assets and overhaul fees, staff education and training fees, labor union funds, etc), mixed costs (management fees, amortization of low-value consumables, water and electricity, and other materials), and shared costs. We used data from the hospital information system in WCH from May 1, 2015, to October 1, 2015. Hospital information system stores demographic data and information about surgeries that are finally carried out by surgeons. In addition, we kept in close touch with clinical experts for further information via both online and face-to-face nonstructured/structured interview. By unifying messy data, deleting or merging repetitive data and simplifying data dimension, we obtained 483 cases of cataract patients, out of whom the most expensive cataract treatment took 13 359.00 CNY, while the cheapest cost 2015.00 CNY, with an average of 6292.29 CNY, as illustrated in Table 1.

**Table 1.** Descriptive Statistics of the Medical Cost of Cataract.

	N	Minimum	Maximum	Mean	Standard deviation	Skewness		Kurtosis	
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	Standard error	Statistics	Standard error
Medical cost	483	2015.00	13 359.00	6292.29	2639.43	0.449	0.194	−0.754	0.385
Effective N					483				

Note. N is the sample size.

Figures 3 and 4 illustrate gender and age distribution of cataract patients. Men are 12.2% more than women, and the average age of all the patients is 61.5 years. Furthermore, more than 81% of the patients range from 51 to 95 years old, indicating that people over the age of 50 years are of high morbidity rate of cataract and should be key monitoring targets. At the same time, the incidence of cataract cannot be ignored for adolescents. It should be noted that 26 children ranging from 1 to 10 years old have cataract in the sample data, accounting for 5.4% of the total number of patients.

Among the cataract medical data collected in this article as shown in Figure 5, 49.7% of the patients have urban basic medical insurance, and 15.9% of the patients are of new rural cooperative medical insurance, and the remaining 34.4% have neither urban basic medical insurance nor rural cooperative medical insurance so as to pay by themselves. In addition, payment source plays a key role in cost analysis. During the treatment of cataract, the economic conditions of the patients will inevitably affect their choice of medical plan, and the payment source of the patient determines his or her actual medical costs. Normally, the patient with urban basic medical insurance or new rural cooperative medical insurance may choose an expensive treatment plan, while the patient who is fully self-funded may consider choosing a cheaper treatment plan, as he or she is relatively less likely to the medical costs which can be partially reimbursed.

In general, intraocular lens (IOL) implantation is a common treatment of cataract. Cataract surgery is to replace the opaque lens of the human eye with a normal artificial lens, so that the eyes can see the light again. IOL is a high-tech product to substitute for turbid crystals after being implanted in the eye. At present, the most commonly used IOL component is made of polymethyl methacrylate, which has high permeability and good biocompatibility, as well as prevents degeneration, irritating effect, and ultraviolet rays. Due to the difference in materials or manufacturing processes, the price of crystals ranges from 1600 to 9000 CNY. According to the price range, we have divided the crystal of 1600 to 3600 CNY, 3600 to 6000 CNY, and those above 6000 CNY into levels of ordinary, better, and best, respectively. Figure 6 illustrates that among the 483 cataract patients, 10.2% of the patients had no IOL implanted because the patients'
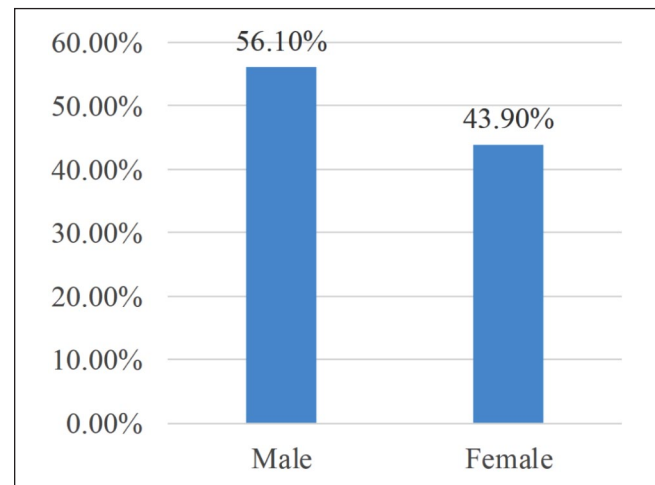
Figure 3. Gender of patients with cataract.

conditions did not require IOL implantation or the patient chose drug therapy instead. The patients that chose to implant ordinary, better, and best crystals account for 37.6%, 33.1%, and 19.1%, respectively. Obviously, more than 70% of patients chose ordinary and better crystals for economic reasons.

Complication refers to the occurrence of another disease or symptom in the course of a disease. The pathogenesis of cataract may also cause other diseases or symptoms. Common cataract complications include vitreous opacity and glaucoma and may be accompanied by other diseases or symptoms. Among the cataract medical data collected in this article, a small number of patients with cataracts are accompanied by complications such as vitreous opacity, glaucoma, and strabismus. According to additional diagnostic analysis as shown is Figure 7, 6.4% of all the patients have suffered from complications including vitreous opacity (53.3%), glaucoma (33.3%), and retinal detachment (13.4%).

Cataract surgery, as one of the most common type of surgery in the ophthalmology department, its duration reflects the level of both doctors and equipment in the hospital. According to Figure 8, the average duration of cataract surgery is 23.97 minutes, and more than 83% of all the surgeries lasted from 10 to 30 minutes.
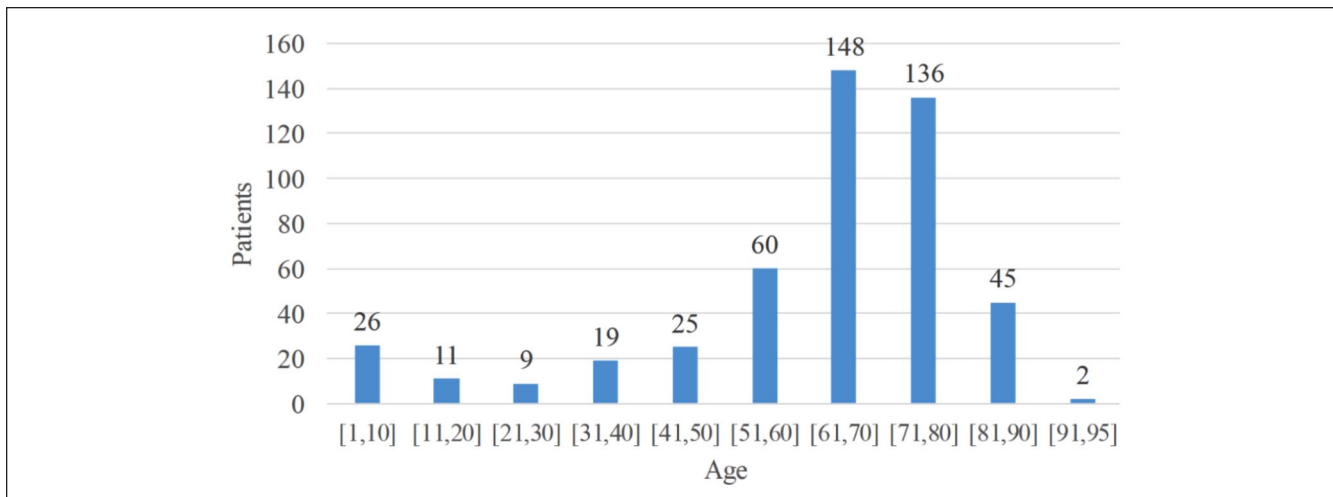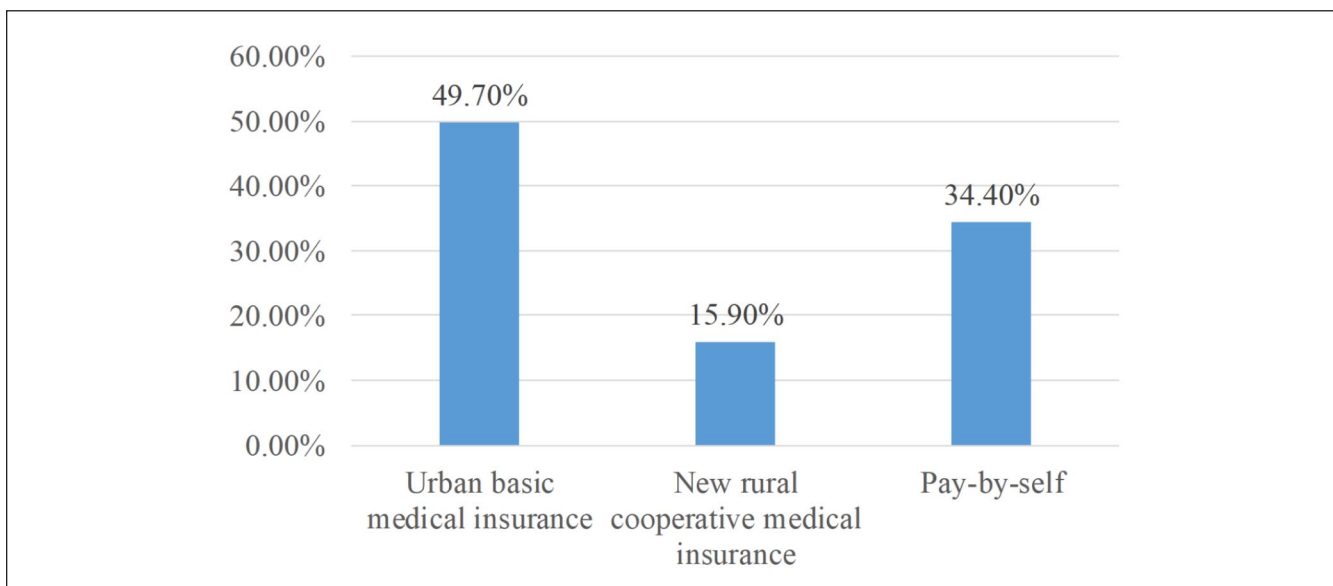
Figure 4. Age of patients with cataract.

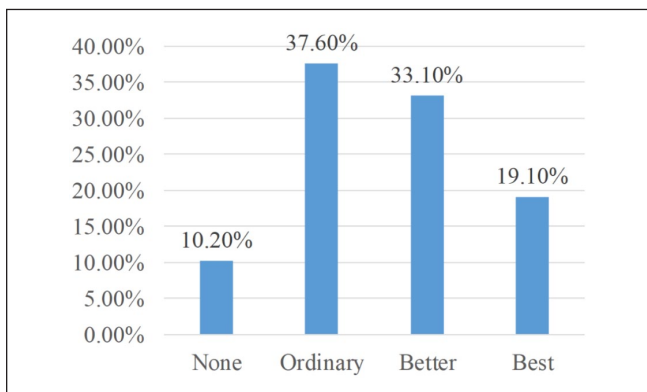**Figure 5.** Payment source.

Figure 6. Intraocular lens implantation type.

We list all these potential driving factors in Table 2, including biological characteristics, economic conditions, pathological characteristics, and medical institutions. In the economic conditions, due to different medical materials, IOLs fall into 4 types, denoted by 0, 1, 2, 3, respectively, and orderly representing implanting nothing, an ordinary, a better, and the best IOL. Cataract can be treated by conducting a surgery, which generally includes 3 types: extracapsular cataract extraction, phacoemulsification, and cataract capsular resection, causing different surgical costs, respectively. Moreover, some patients may suffer from comorbidities such as cataract and glaucoma, vitreous and strabismus, which affect both the complexity of the operation and the medical costs. Table 2 shows the candidate influencing factors of the cost of cataract.
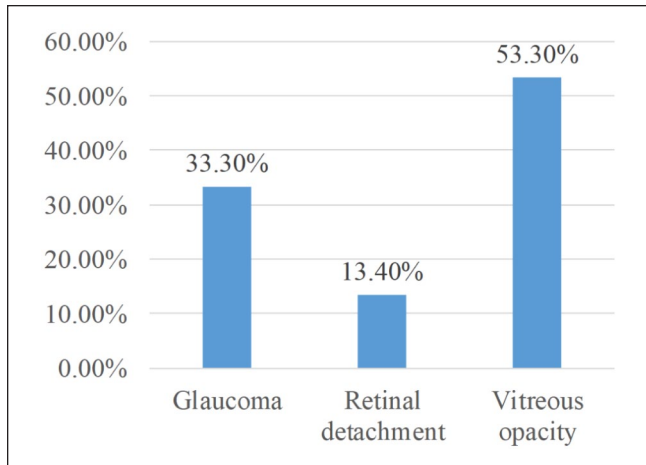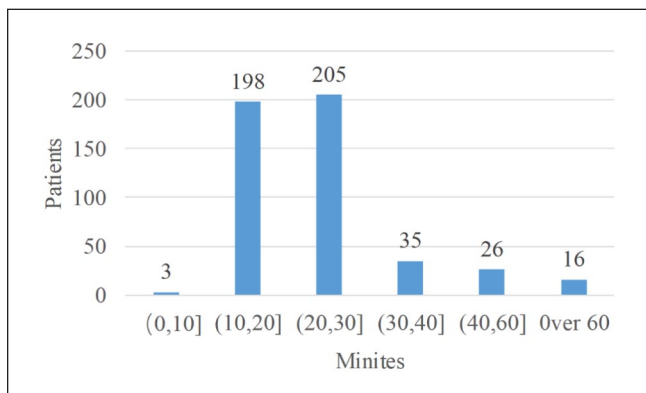
Figure 7. Comorbidities of cataract.

Figure 8. Duration of cataract surgery.

Cost Forecasting and Results

Cost Forecasting by MRA

Correlation analysis of influencing factors. The existence and rough quantification of correlation between variables can be illustrated by making related graphs or related tables in basic statistical analysis. However, correlation coefficient method can accurately measure the strength of the relationship between variables.

Commonly used correlation analysis methods are Pearson simple correlation coefficient, Spearman rank correlation coefficient, Kendall rank correlation, and partial correlation. Pearson is applicable to the equal interval measure, while Spearman and Kendall are suitable for the nonparametric measure.

In general, Pearson can reflect the degree of linear correlation between variables in multivariable regression models, hence it was used to analyze and estimate the linear correlation between cataract medical cost and its influencing factors. The hypothesis test of overall correlation coefficient ρ is $H_0: \rho = 0$, indicating no correlation between the variables, while the alternative hypothesis is $H_1: \rho \neq 0$, indicating the existence of correlation between the variables.

And SPSS21.0 was used in our study, the results are shown in Table 3. It can be concluded that factors influencing cost of cataract in the MRA include, in importance order, IOL implantation ($|r|$: 0.805, $P < .01$), doctor level ($|r|$: 0.644, $P < .01$), payment source($|r|$: 0.554, $P < .01$), admission status($|r|$: 0.326, $P < .01$), additional diagnosis ($|r|$: 0.260, $P < .01$), type of surgery ($|r|$: 0.127, $P < .05$), and type of anesthesia ($|r|$: 0.126, $P < .05$).

Parameter estimation. According to above analysis, total medical cost of cataract is not significantly influenced by factors including gender, age, and duration of surgery. Hence, we selected the remaining factors as independent variables, while the total medical cost of cataract patients as the dependent variable, to model multivariable regression by SPSS21.0. Results are shown in Table 4. The value of adjusted R^2 of the regression model is equal to 0.979, and the value of Durbin-Watson is 1.352, indicating high goodness of fit and no sequence autocorrelation, respectively.

Furthermore, in Table 5, the F value of the regression model is 1040.996, and the corresponding P value is .000, which is less than the significant level of .05, indicating that the part of each influencing factor explained to the medical cost of cataract is significant.

Moreover, the regression coefficients of the multivariable linear regression model and the corresponding statistics are shown in Table 6. The value of the constant is 1521.223, and the corresponding P values are less than .05, indicating significance of each regression coefficients, which is consistent with the variance analysis in Table 5. At the same time, the value of VIF is less than 10, excluding the existence of multicollinearity. The regression model can be written as follows:

$$Y = 1521.223 + 374.116X_1 + 1034.691X_2 + \\ 1359.437X_3 + 463.169X_4 - 876.111X_5 + \\ 1436.552X_6 + 1407.857X_7,$$

where Y is the total medical cost, and $X_1, X_2, \ldots, X_7$ are a type of surgery, doctor level, type of IOL implantation, anesthesia method, payment source, admission status, and additional diagnosis, respectively.

Test of goodness of fit and parameters. The residual statistics are given in Table 7. The minimum value of the residuals obtained is –871.911, and the maximum value is 1012.524, with 0 as the mean of the residuals. Figures 9 and 10 illustrate the histogram and standard P-P plot of the standardized residuals, both satisfying the basic assumption of normal distribution, hence demonstrating the reliability of the model.

Cost Forecasting by BPNN

A 3-layer network is used in our study, including an input layer with n ($n = 10$) neurons representing the 10 influencing factors of the total medical cost of cataract, an hidden layer with l ($l = 21$) neurons, and an output layer with only 1

Table 2. Variables or Influencing Factors of the Medical Cost of Cataract.

Category	Influencing factor	Description
Biological characteristics	Gender	0 = female, 1 = male
	Age	[1, 95]
Economic conditions	Payment source	1 = urban basic medical insurance, 2 = new rural cooperative medical insurance, 3 = pay-by-self
	Type of anesthesia	0 = local anesthesia, 1 = general anesthesia
	IOL implantation type	0 = No, 1 = ordinary, 2 = better, 3 = best
Pathological characteristics	Type of surgery	1 = extracapsular cataract extraction, 2 = cataract phacoemulsification, 3 = cataract capsular resection
	Admission status	0 = general, 1 = serious
	Additional diagnosis	0 = no, 1 = complication
Medical institutions	Doctor level	1 = attending physician, 2 = deputy chief physician, 3 = chief physician
	Duration of surgery	Continuous variable
Medical cost		Continuous variable

Note. IOL = intraocular lens.

Table 3. Pearson Correlation Analysis.

	Gender	Age	Type of surgery	Doctor level	Duration of surgery	IOL implantation type	Type of anesthesia	Payment source	Admission status	Additional diagnosis	Total medical cost
Medical cost											
Pearson correlation	−.043	.086	.127*	.644**	−.028	.805**	.126*	−.554**	.326**	.260**	1
Significance (unilateral)	.296	.143	.047	.000	.362	.000	.047	.000	.000	.000	
N	483	483	483	483	483	483	483	483	483	483	483

Note. IOL= intraocular lens.
*Significantly correlated at .05 level (one side). **Significantly correlated at .01 level (one side).

Table 4. Model Summary.

Serial number	R	R^2	Adjusted R^2	Standard estimated error	Durbin–Watson
1	.990[a]	.980	.979	382.29958	1.352

Note. Dependent variable: medical cost of cataract.
[a]Predictive variables: (constant), additional diagnosis, intraocular lens implantation, type of surgery, admission status, type of anesthesia, payment source, and doctor level.

Table 5. Analysis of Variance.

Serial number		Quadratic sum	df	Mean square	F	Significance
1	Regression	1 065 012 165.724	7	152 144 595.103	1040.996	.000[a]
	Residual	21 776 792.332	475	146 152.969		
	Total	1 086 788 958.056	482			

Note. Dependent variable: medical cost of cataract.
[a]Predictive variable: (constant), additional diagnosis, intraocular lens implantation, type of surgery, admission status, type of anesthesia, payment source, and doctor level.

Table 6. Coefficient.

Serial number		Unstandardized coefficients		Standard coefficient				Collinear statistic	
		B	Standard error	Trial	t	Significance	95% CI	Tolerance	VIF
I	(Constant)	1521.223	202.224		7.522	.000	(1123.853 to 1918.593)		
	Type of surgery	374.116	38.134	.115	9.811	.000	(299.183 to 449.049)	.985	1.015
	Doctor level	1034.691	46.831	.292	22.094	.000	(942.668 to 1126.714)	.772	1.295
	IOL implantation type	1359.437	30.791	.582	44.150	.000	(1298.933 to 1419.941)	.775	1.291
	Type of anesthesia	463.169	64.529	.086	7.178	.001	(336.370 to 589.968)	.947	1.056
	Payment source	−876.111	41.190	−.266	−21.270	.000	(−957.0494 to 795.173)	.862	1.160
	Admission status	1436.552	63.848	.264	22.500	.000	(1311.091 to 1562.0133)	.980	1.020
	Additional diagnosis	1407.857	65.360	.252	21.540	.000	(1279.425 to 1536.289)	.984	1.016

Note. Dependent variable: medical cost of cataract. CI = confidence interval; VIF = variance inflation factor; IOL = intraocular lens.

Table 7. Residual Statistic.

	Minimum	Maximum	Mean	Standard deviation	N
Predicted value	2015.0935	12346.4766	6292.2877	2612.85305	483
Residual	−871.91046	1012.52374	0.00000	373.62391	483
Normal expected value	−1.637	2.317	0.000	1.000	483
Standardized residual	−2.281	2.649	0.000	0.977	483

Note. Dependent variable: medical cost of cataract.

neuron representing the total medical cost, wherein l and n satisfy the formula $l = 2n + 1$, and the BPNN topology constructed in this way is $10 \times 21 \times 1$ (as shown in Figure 11).

In the BPNN, the input data were first preprocessed and normalized to reduce the difference in magnitude, and the initial weights and thresholds were random. Furthermore, the updating of weights and thresholds was based on the forecasting error e_k (equal to the difference between the forecast and actual value), and learning rate η. Meanwhile, the updating of network connection weights, ω_{ij} and ω_{jk}, relies on e_k, with formula written as

$$\omega_{ij} = \omega_{ij} + \eta R_j \left(1 - R_j\right) x(i) \sum_{k=1}^{m} \omega_{jk} e_k$$
$$i = 1, 2, \ldots, n; \ j = 1, 2, \ldots, l;$$
$$\omega_{jk} = \omega_{jk} + \eta R_j e_k \ j = 1, 2, \ldots, l; \ k = 1, 2, \ldots, m,$$

where i, j, k are the input layer, hidden layer, and output layer, respectively.

And the updating of the thresholds also relies on e_k to update the network connection weights a_j and b_k:

$$a_j = a_j + \eta R_j \left(1 - R_j\right) \sum_{k=1}^{m} \omega_{jk} e_k \ j = 1, 2, \ldots, l;$$
$$b_k = b_k + e_k \ k = 1, 2, \ldots, m.$$

The training of the neural network will terminate if the forecasting error reaches a set value. And in our study, the
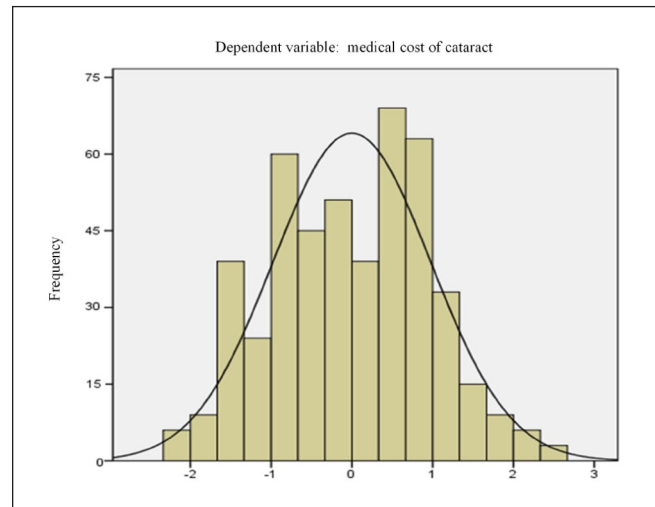

Figure 9. Histogram of standardized residuals.

transferring of signal in neurons of single input, hidden, and output layer obeyed "tansig," "tansig," and "purelin" function, respectively, while the training of BPNN adopted "traingdx" function. Moreover, language programming and MATLAB neural network toolbox were used to train the network. Before training, the number of steps in 1 result, the learning rate, the maximum number of training steps and the target value of forecasting error of BPNN were set 100, 0.01, 1×10^5, and 6×10^{-4}, respectively. After 58134 trainings,
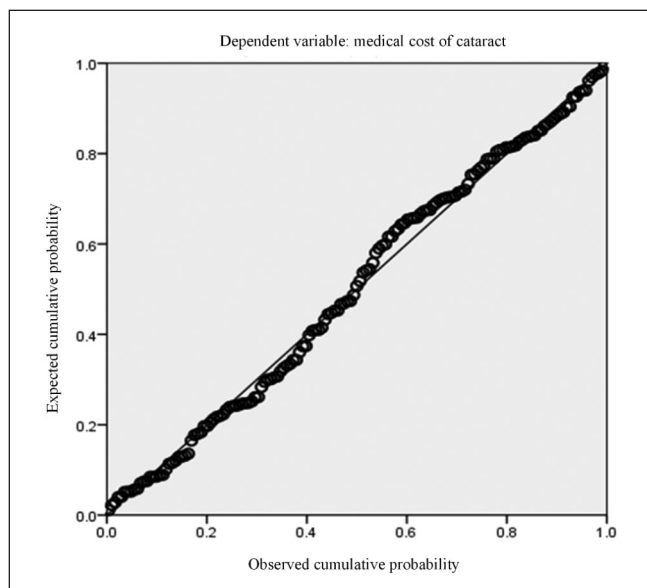
Figure 10. Standard P-P diagram of standardized residuals.

the neural network realized its target forecasting error, whose curve is shown in Figure 12.

Forecasting Performance of the Proposed Models

Table 8 is presented to compare the forecasting performance of the 2 models by randomly selecting 10 cases from the total 483 records. Obviously, both BPNN and MRA can be applied for single disease cost forecasting, with the absolutes of percentage error of the former less than 6%, while those of percentage error of the latter meeting 10%. Furthermore, the average forecasting error of BPNN is 2.81%, while that of MRA is 5.79%, indicating better generation ability of BPNN than that of MRA.

Discussion

This article had 2 objectives. First was to identify the driving factors of medical cost of cataract, thus some implications or insights about causes and corresponding measures might be obtained. Second was to compare the performance of 2 forecasting models to anticipate medical cost forecasts, which can provide a reference value for medical service pricing under the mode of charge according to the disease.

To answer our first objective, we identified the driving factors of cataract cost by Pearson correlation in MRA, in importance order, including (1) IOL implantation, (2) doctor level, (3) payment source, (4) admission status, (5) additional diagnosis, (6) type of surgery, and (7) type of anesthesia. According to hospital managers, these factors fall into 2 categories intuitively, 1 is related to the patient's own (factors 1, 3, 4, 5, 6, and 7) and the other is from the medical institution (factor 2). It indicates that both patients and

hospitals are of potential to monitor those driving factors to engage in cost controlling.

From the perspective of patients, results indicate that the medical cost is closely related to patient's economic conditions (factors 1, 3, and 7) and pathological characteristics (factors 4, 5, and 6), while irrelevant with patient's biological characteristics in statics (gender and age).

Regarding the patient's economic conditions, hospital data show some significant differences in medical costs among patients with urban basic insurance, new rural cooperative medical insurance, and pay-by-self. Because patients with urban basic insurance or new rural cooperative medical insurance can reimburse some medical expenses, their economic conditions are less considered when doctors applying medical materials and products, while for self-paying patients, economic limits must be considered when choosing medical materials and medicines.

With respond to pathological characteristics of the patient, the onset time and severity of the disease will inevitably affect its medical cost. Kiridly et al[36] demonstrated that the severity of a patient's illness correlates with increased costs. Furthermore, in their cohort of patients who had the most serious comorbidities, results indicated a cost burden of above 18% while only accounting for 1.1% of the study population. In general, the longer the onset time is, the greater its impact on the patient, and may affect the normal functioning of other parts of the patient's body or cause complications. The medical costs of patients with severe illness and emergent hospital admission are generally higher than those of ordinary outpatients admitted to hospital. It is mainly due to the difference in clinical pathways taken by the hospital in the case of serious illness or emergency. With both prevalence of smart health care tools (ie, applications in smart phones like cataract assistant, an app developed by one of the largest medical health service website in China—XYWY. net) and trend of patients' participation and cooperation, considering smart tools might play an important role in subsequent medical costs control, we recommend that patients be self-educated and smart to activate disease treatment, diagnosis, prevention, and management. To be more specific, a smart patient is proactive in his or her own health management: with the existed reliable health information to make evidence-informed choice, use diversified smart technologies to perform self-monitoring, self-care, and equal involvement in clinical decision-making, to get best and most appropriate treatment and better manage costs.[37] It is worth noting that patient education plays a key role in the realization of the wisdom of smart patients, in addition to self-education, the role of institutions like hospitals and government, and how they operate in patient education are still the problems to be solved currently.

Moreover, it is known that certain characteristics of the patient's own such as gender and age[38,39] may have an impact on medical costs during the course of treatment. Generally, patient's age and medical cost show a relationship of smile
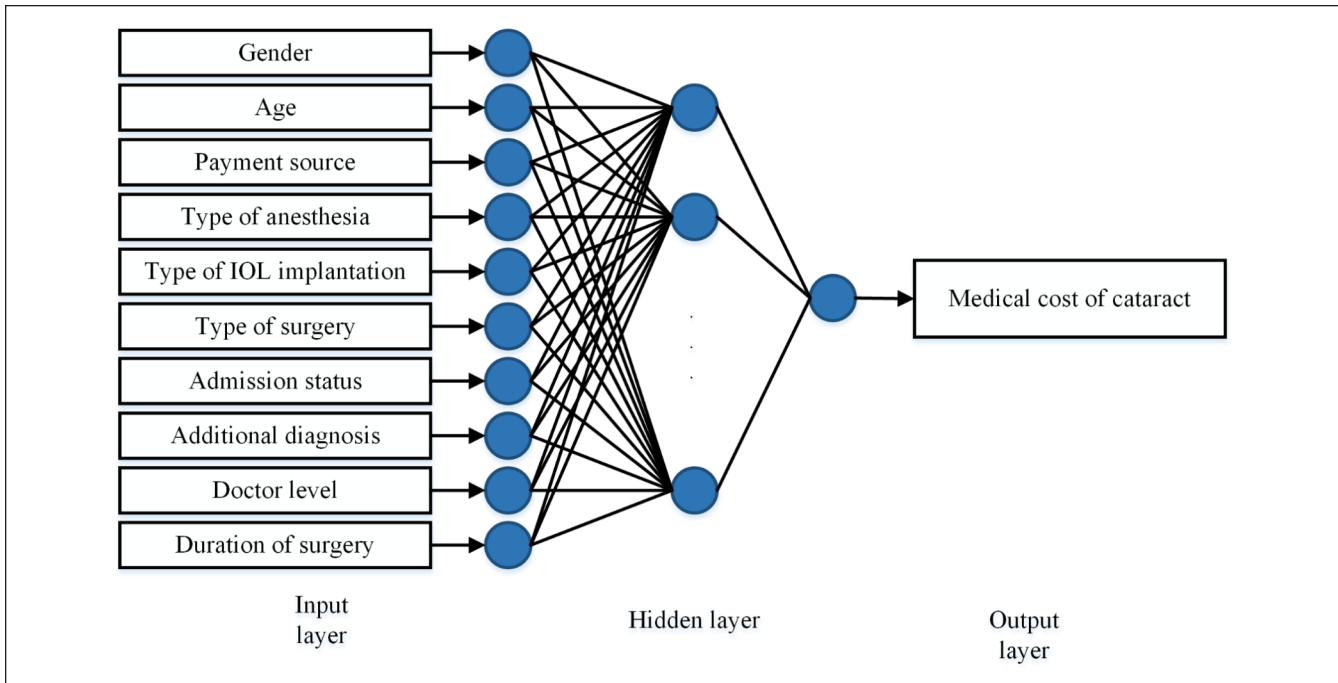
Figure 11. Backpropagation neural network (BPNN) for forecasting the medical cost of cataract $(N^{(10\times21\times1)})$.
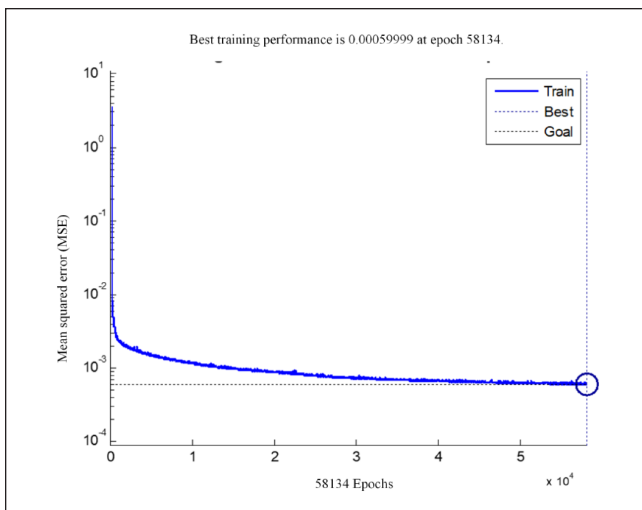*Note.* IOL = intraocular lens.

Figure 12. Training of forecasting error.

curve which means that higher or lower the patient's age is, the higher the medical cost is, for the relatively poor immunity of the elderly and children, and their greater difficulty to recover from the disease, prolonging the treatment time and length of stay inevitably. However, in terms of cataract, results in our study indicate that its medical cost is not influenced by age and gender significantly. There is no clear conclusion for as to why this happens. However, according to an interview with the head nurse in the ophthalmology department, cataract surgery in WCH can be performed with micro incisions compared with previous surgical techniques for

removing cataract, further promoting faster healing and reducing the risk of cataract surgery complications, such as uveitis, retinal detachment, and pupil block. Hence, it can be performed on an outpatient basis and does not require an overnight stay in a hospital or other care facility. After surgery, patients can expect his or her vision to begin improving within a few days.

From the perspective of hospital, significant factors affecting the medical cost of the disease include hospital level (tertiary hospitals and provincial hospitals charge more expensive), medical technology, and service quality. These factors cause a large proportion of the medical cost of the disease. Superb medical technology and meticulous care can promote the early recovery of patients, and reduce the possibility of infection or other complications. Furthermore, it can also decrease the likelihood of readmission of patients to reduce the cost of the disease. At the same time, the doctor's expertise or doctor level is another vital factor influencing the cost of the disease, for different levels of doctors occupying different resources of the hospital, leading to variation in visiting cost. However, duration of cataract surgery demonstrates insignificant impact on its medical cost, which is opposite to results obtained by Vonlanthen et al[40] and Chu et al[41] because in our cooperation hospital and other hospitals we surveyed, cost accounting is mostly based on clinical pathway or service items, and time-related costing methods like time-driven activity-based costing (TDABC) are just in infancy, which is of potential in cost control. For this situation, the hospitals should take certain measures to support and encourage the study of customized-implementation of

Table 8. Comparison of Forecasting Performance of MRA and BPNN.

Number	Actual value	MRA forecast	Error	Percentage error	BPNN forecast	Error	Percentage error
1	5004.96	5266.66457	261.71	5.23	5193.645098	188.69	3.77
2	9284.10	8812.28161	−471.82	−5.08	9412.361191	128.26	1.38
3	3127.20	3422.95046	295.75	9.46	3037.877296	−89.32	−2.86
4	13359	12346.47623	−1012.52	−7.58	13503.11546	144.12	1.08
5	8267.2	7716.79984	−550.40	−6.66	8010.429492	−256.77	−3.11
6	2015	2104.14625	89.15	4.42	2124.993867	109.99	5.46
7	6590.36	6771.25421	180.89	2.74	6448.817924	−141.54	−2.15
8	5463.95	5818.02862	354.08	6.48	5606.964064	143.01	2.62
9	10396.8	10564.50312	167.70	1.61	10587.42608	190.63	1.83
10	8851	8081.32218	−769.68	−8.69	8507.274468	−343.73	−3.88

Note. MRA = multivariable regression analysis; BPNN = backpropagation neural network.

the likely beneficial time-related costing methods. After applying TDABC to 3 different medical-surgical procedures, Martin et al[42] proposed that the application of TDABC can identify rate-limiting steps, minimize redundancy, and may generate cost savings. These cost savings are a direct result of improved efficiency and the alignment of provider skill set with a given task.

In addition, with respect to modifiable cost driving factors, we suggest hospital optimize patient/caregiver education with short videos or booklets instead of current none/limited instruction to avoid readmission and corresponding costs, which is demonstrated essential in chronic disease management in broad studies.[43-45]

In answering our second objective, we compared the performance of MRA and BPNN by modeling our data set of 483 records using SPSS21.0 and MATLAB 2015a, respectively. Backpropagation neural network can predict single disease cost well with forecasts approximating actual values. All of the percentage errors of both BPNN and MRA are less than 10%, indicating their applicability to forecasting. But the average error of MRA is slightly higher than that of BPNN, demonstrating advantage of the latter over the former. We therefore concluded that both MRA and BPNN are technically and economically feasible in generating medical cost of cataract. As MRA is more convenient with simple and practical operation, while BPNN is technically complicated, we suggest hospitals choose either model according to their different expertise and demand. After anticipating acceptable cost forecasts scientifically, the cost level and trend could be reasonably set by hospital decision makers, which is helpful in formulating the fixed payment standard for each disease under the mode of charging according to the disease.

There were 5 principal limitations of our study. First, estimated model parameters reflect the costs of the particular hospital—WCH, and at a particular duration in time. Such models cannot be applied directly with the same parameters to all the hospitals, instead require parameter re-estimation. Second, we focused on single disease and piloted in cataract, for its simpler diagnosis and treatment process as well as fewer complications than other diseases. Future research should extend from single disease to DRGs. Third, cataract was the only disease we take into consideration, hence such conclusion as medical cost was not affected by "patient's gender," "patient's age," and "duration of surgery" significantly might not be valid to other diseases. Fourth, there are still a number of influencing factors in the real world. For the unavailability of data, factors like patient's household income, patient's family area, and patient's education background had not been taken into account. Actually, these factors may influence the decisions of both patients and surgeons. Fifth, for the fact that every single model has its bias on the forecasting, some hybrid models should be built to avoid the bias and improve the forecasting accuracy.

Despite these limitations, our study has a number of strengths. To the best of our knowledge, this study extends previous work by exploring driving factors of medical cost specifically and exclusively for single disease. Existing cost forecasting in health care is mainly on identifying potential high-cost patients, forecasting total health care costs, evaluating expected population costs for contract pricing and premium setting, and individualized assessment of cost impacts of predictors, when it comes to single disease cost, there is little analysis according to literature review. Moreover, regarding the technically complexity, this article provides evidence on the applicability of BPNN as a better decision support tool over the linear alternative to forecast single disease cost.

Conclusion

This article examines the issue of forecasting single disease costs by collecting medical data of cataract patients in WCH, exploring the factors influencing the medical costs of those patients and forecasting cataract cost with MRA and BPNN, respectively. According to the results, driving factors from patients like admission status and additional diagnosis present challenges to managing medical costs, we suggest that smart patients in the future be of potential to contribute to

cost controlling. Second, both MRA and BPNN are technically and economically feasible in generating medical cost of cataract. And we suggest hospitals choose either model according to their expertise and demand.

Therefore, single disease cost forecasting, as an effective way of feed-forward control for medical institutions to carry out cost management, can predict the trend of medical cost indicators and provide effective information for dynamic control of medical costs. In addition, for hospitals, single disease cost forecasting also works in medical cost control. First, it can help medical institutions dynamically monitor the medical cost control of each patient and conduct exception management for those patients whose medical costs exceed the fixed rate of reimbursement to reduce their medical costs. Second, it provides reference values for scientifically formulating the fixed payment standard for each disease in terms of charging according to the disease by reasonable forecasting single disease cost, thus avoiding abuse of medical service, preventing over medical treatment, and ensuring the quality of medical services.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

Ethical Approval

The study does not involve human subjects and adheres to all current laws of China.

ORCID iD

Chuang Liu https://orcid.org/0000-0002-5573-738X

References

1. Department of Health and Aging Australia. *The Review of the AR-DRG Classification System Development Process*: Brisbane, QLD, Australia: PricewaterhouseCoopers; 2009.
2. Klein-Hitpass U, Scheller-Kreinsen D. Policy trends and reforms in the German DRG-based hospital payment system. *Health Policy*. 2015;119(3):252-257.
3. Rochell B, Roeder N. DRG: the new hospital reimbursement system for Germany. *Urologe A*. 2003;42(4):485-495.
4. Paat-Ahi G, Aaviksoo A, Swiderek M. Cholecystectomy and diagnosis-related groups (DRGs): patient classification and hospital reimbursement in 11 European countries. *Int J Health Policy Manag*. 2014;3(7):383-391.
5. Hanley GE, Morgan S, Reid RJ. Explaining prescription drug use and expenditures using the adjusted clinical groups case-mix system in the population of British Columbia, Canada. *Med Care*. 2010;48(5):402-408.
6. Wang K, Li P, Chen L, Kato K, Kobayashi M, Yamauchi K. Impact of the Japanese diagnosis procedure combination-based payment system in Japan. *J Med Syst*. 2010;34(1):95-100.
7. Wang YD, Song B. Improve management level by promoting medical cost forecasting. *Chinese Health Econ*. 1998;5:58.
8. Ukponmwan CU, Omoti AE, Uhunmwangho OM. Reducing the barriers to the uptake of cataract surgical services in a tertiary hospital. *Orient J Med*. 2010;22(1-4):16-19.
9. Anderson DF, Dhariwal M, Bouchet C, Keith MS. Global prevalence and economic and humanistic burden of astigmatism in cataract patients: a systematic literature review. *Clin Ophthalmol*. 2018;12:439-452.
10. Wang J, Jin L, Lu Q, et al. Barriers, costs, and attitudes toward pediatric cataract surgery at two large facilities in China and India. *Ophthalmic Epidemiol*. 2019;26(1):47-54.
11. Binnawi KH, Abdu M. Barriers to the uptake of cataract surgical services in Sudan: a population based study in Kassala State. *Sudanese J Ophthalmol*. 2015;7(1):10-12.
12. Ono K, Hiratsuka Y, Murakami A. Global inequality in eye health: country-level analysis from the global burden of disease study. *Am J Public Health*. 2010;100(9):1784-1788.
13. Bongaarts J. Human population growth and the demographic transition. *Philos Trans R Soc Lond B Biol Sci*. 2009;364(1532):2985-2990.
14. Zhao XM. One-way regression and grey prediction GM (1,1) for forecasting project cost. *J North China Electric Power Univ*. 2011;2:114-117.
15. Alshamrani OS. Construction cost prediction model for conventional and sustainable college buildings in North America. *J Taibah Univ Sci*. 2016;11(2):315-323.
16. Shahandashti SM, Ashuri B. Highway construction cost forecasting using vector error correction models. *J Manag Eng*. 2016;32(2):1943-5479.
17. Kim BC. Integrating risk assessment and actual performance for probabilistic project cost forecasting: a second moment Bayesian model. *IEEE Trans Eng Manag*. 2015;62(2):158-170.
18. Sun ZN. *The Prediction of Railway Freight Cost Based on Cost Driver and BP Neural Network* [master's thesis], Beijing, China: Beijing Jiaotong University; 2012.
19. Ficko M, Drstvensek I, Brezocnik M, Balic J, Vaupotic B. Prediction of total manufacturing costs for stamping tool on the basis of cad-model of finished product. *J Mater Process Technol*. 2005;164:1327-1335.
20. Chu S, Majumdar A. Opportunities and challenges for a sustainable energy future. *Nature*. 2012;488(7411):294-303.
21. Wang F. *Study on Cerebral Infarction Hospitalization Expenditure and Its Influencing Factors in a Tertiary Teaching Hospital* [master's thesis], Jinan, China: Shandong University; 2013.

22. Bates DW, Saria S, Ohno-Machado L, Shah A, Escobar G. Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Aff*. 2014;33(7):1123-1131.

23. Hong CS, Siegel AL, Ferris TG. Caring for high-need, high-cost patients: what makes for a successful care management program. *Issue Brief (Commonw Fund)*. 2014;19:1-19.

24. Lin SC, Zhang QP, Chen F, Luo L, Chen L, Zhang W. Smooth Bayesian network model for the prediction of future high-cost patients with COPD. *Int J Med Inform*. 2019;126:147-155.

25. Zhao Y, Ash AS, Ellis RP, et al. Predicting pharmacy costs and other medical costs using diagnoses and drug claims. *Med Care*. 2005;43(1):34-43.

26. Bertsimas D, Bjarnadottir MV, Kane MA, et al. Algorithmic prediction of health-care costs. *Oper Res*. 2008;56(6):1382-1392.

27. Duncan I, Loginov M, Ludkovski M. Testing alternative regression frameworks for predictive modeling of healthcare costs. *N Am Actuar J*. 2015;20(1):1-23.

28. Hodgman SB. Predictive modeling and outcomes. *Prof Case Manag*. 2008;13(1):19-23.

29. Ramamurthy KN, Wei D, Ray E, et al. A configurable, big data system for on-demand healthcare cost prediction. Proceedings of the IEEE International Conference on Big Data (Big Data); 11-14 December 2018; Boston, MA.

30. Wrathall JA, Belnap T. Reducing health care costs through patient targeting: risk adjustment modeling to predict patients remaining high cost. *EGEMS*. 2017;5(2):4-8.

31. Munoz-Price LS, Hota B, Stemer A, Weinstein RA. Prevention of bloodstream infections by use of daily chlorhexidine baths for patients at a long-term acute care hospital. *Infect Control Hosp Epidemiol*. 2009;30(11):1031-1035.

32. Zupancic JA, Richardson DK, O'Brien BJ, Schmidt B, Weinstein MC. Daily cost prediction model in neonatal intensive care. *Int J Technol Assess Health Care*. 2003;19(2):330-338.

33. Swierkowski P, Barnett A. Identification of hospital cost drivers using sparse group lasso. *PLOS ONE*. 2018;13(10):e0204300.

34. Popesko B, Papadaki S, Novák P. Cost and reimbursement analysis of selected hospital diagnoses via activity-based costing. *Ekonomika Manag*. 2015;18(3):50-61.

35. Zhang RQ, Pei HB, Wang MZ, Lu YJ. Application of regression model to predict hospitalization expenses for esophageal cancer. *Chin J Health Stat*. 2009;26(4):417-418.

36. Kiridly DN, Karkenny AJ, Hutzler LH, Slover JD, Iorio R, Bosco JA. The effect of severity of disease on cost burden of 30-day readmissions following total joint arthroplasty (TIA). *J Arthroplasty*. 2014;29(8):1545-1547.

37. Chen YL, Yang L, Hu H, Chen JJ, Shen BR. How to become a smart patient in the era of precision medicine? In: Shen B, ed. *Healthcare and Big Data Management*. Singapore: Springer; 2017:1-16.

38. Robinson TN, Wu DS, Stiegmann GV. Frailty predicts increased hospital and six-month healthcare cost following colorectal surgery in older adults. *Am J Surg*. 2011;202(5):511-514.

39. Yu W, Ravelo A, Wagner TH, Barnett PG. The relationships among age, chronic conditions, and healthcare costs. *Am J Manag Care*. 2004;10(12):909-916.

40. Vonlanthen R, Slankamenac K, Breitenstein S, et al. The impact of complications on costs of major surgical procedures: a cost analysis of 1200 patients. *Ann Surg*. 2011;254(6):907-913.

41. Chu D, Bakaeen FG, Wang XL, LeMaire SA, Coselli JS, Huh J. Does the duration of surgery affect outcomes in patients undergoing coronary artery bypass grafting. *Am J Surg*. 2008;196(5):652-656.

42. Martin JA, Mayhew CR, Morris AJ, Bader AM, Tsai MH, Urman RD. Using time-driven activity-based costing as a key component of the value platform: a pilot analysis of Colonoscopy, aortic valve replacement and carpal tunnel release procedures. *J Clin Med Res*. 2018;10(4):314-320.

43. Khasawneh A. Guidelines for comparing interventions, predicting high risk patients, and conducting optimization for early HF readmission [dissertation, Electronic Theses & Dissertations Center]. Akron, OH: University of Akron; 2017. https://etd.ohiolink.edu/. Accessed June 20, 2019.

44. Kripalani S, Theobald CN, Anctil B, Vasilevskis EE. Reducing hospital readmission rates: current strategies and future directions. *Annu Rev Med*. 2014;65:471-485.

45. Peter D, Robinson P, Jordan M, Lawrence S, Casey K, Salas-Lopez D. Reducing readmissions using teach-back: enhancing patient and family education. *J Nurs Adm*. 2015;45(1):35-42.