# Total Health Expenditure and Its Driving Factors in China: A Gray Theory Analysis

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# Total health expenditure and its driving factors in China: a gray theory analysis

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**Abstract**

**Background:** The continuous growth in total health expenditure (THE) has become a social issue of common concern in most countries. In China, THE is maintaining a rapid growth trend that is faster than that of the economy, and this trend has become increasingly obvious in the 21st century and has placed a heavy burden on the government and residents. Therefore, the aims of this paper are to analyze the main driving factors and establish a predictive model of the growth of THE in China in the 21st century.

**Methods:** Gray system theory was employed to explore the correlation degree between THE and 9 hot topics in the areas of the economy, population, health service utilization, and policy using national data for China from 2000 to 2018. Additionally, a New Structure of the

Multivariate Gray (NSGM) prediction model of health expenditure was established and compared with the traditional grey model and widely used Back Propagation (BP) neural network.

**Results:** General government expenditures on health, the economy, and out-of-pocket health expenditures were highly correlated with THE, with all correlation degrees greater than 0.8. The correlation degrees between health institutions, population and THE were 0.6-0.8, whereas infant mortality rate and THE was only 0.573. The average of the residual percentage of the training data of the NSGM(1,10) model is 0.36%, and that of the test data is 1.85%, which is better than the results of the other models.

**Conclusion:** The Chinese government and society have played a crucial role in reducing residents' medical burden, whereas the improved economy and aging population have increased the demand for health services, leading to the continual increase in THE. The improved NSGM(1,N) model achieved good prediction accuracy and has unique advantages in simulating and predicting THE, which can provide a basis for policy formulation.

**Keywords:** Health expenditure; Socioeconomic factors; Predictions and projections; Demography; Public policy

**Additional non-English language abstract**

**摘要**

**背景：**卫生总费用的持续增长已成为大多数国家共同关注的社会问题。在中国，卫生总费用的增长速度已经超过经济的增长速度，这种趋势在 21 世纪变得更加明显，给政

府和居民带来了沉重的负担。因此，本文的目的是分析 21 世纪中国卫生总费用增长的主要驱动因素，并建立卫生总费用增长的预测模型。

**方法：**基于灰色系统理论，利用 2000-2018 年中国国家数据，探讨卫生总费用与经济，人口，卫生服务利用和政策等 9 个热点话题之间的相关程度。同时，建立卫生总费用的多元灰色预测模型（NSGM），并将其与传统的灰色模型和应用较为广泛神经网络模型进行比较。

**结果：**广义政府卫生支出，个人现金卫生支出经济因素和与卫生总费用高度相关，相关程度大于 0.8。卫生机构和人口因素与卫生总费用的相关程度在 0.6-0.8 之间，而婴儿死亡率与卫生总费用的相关程度仅为 0.573。NSGM（1,10）模型训练数据的残差百分比平均值为 0.36%，而测试数据的残差百分比平均值为 1.85%，模型拟合结果优于其他模型。

**结论：**中国政府和社会在减轻居民医疗负担方面发挥了关键作用，然而经济的改善和人口的老龄化的加剧增加了居民对于医疗服务的需求，导致中国卫生总费用持续增长。改进的 NSGM（1，N）模型具有良好的预测精度，在模拟和预测卫生总费用方面具有独特的优势，可以为制定政策提供依据。

## 1 Background

Across economic development and healthcare settings, it is increasingly recognized that improving living and health standards is important, and improving health is a growing concern. At the same time, the continuous growth in total health expenditure (THE) and the associated economic burden, as an internationally recognized indicator, have become social issues of common concern in most countries [1-4], reflecting countries' investment and burden in the health field from a society-wide perspective. According to the most recent data from the Organization for Economic Cooperation and Development (OECD), at the beginning of the 21st century, the proportion of health expenditure of the gross domestic product (GDP) of its member states rose from 7.0% in 2000 to 8.8% in 2019, and the per capita health expenditure in its member states also increased rapidly. For example, the proportion of health expenditure in US GDP rose by 4.42% to 17.0%, ranking first in the world, and per capita medical and health expenditure increased by 142.95% to $11,071 [5]. However, Fredell MN [4] Pointed out that despite spending approximately 18% of GDP—more than $3.2 trillion—on health care (vs 6-12% in other developed countries), the United States ranks poorly in terms of objective healthcare measures. In another large economic community, the European Union, THE has been increasing sharply over the past two to three decades. On the one hand, THE more than doubled in real terms between 1995 and 2010, and on the other hand, it is still increasing along a continuous and rather stable trend line [6]. Therefore, how to control unreasonable increases in health expenses is an important issue that urgently needs a solution. In this respect, it is necessary to better understand the main driving factors of growth and establish predictive models to grasp the trend of changes in THE so that governments can identify areas for future intervention.

Research on THE is extensive, and the research methods vary. The main driving factors are demographics [7], economics [6, 8], and disease [9]. Scholars [10, 11] have also analyzed the relationships between education and health expenditure, air quality and health expenditure, and environment and health expenditure. Because of fundamental differences in the health systems, economic levels, population health, ideologies, cultures and regional environments of different countries and large disparities in the size and growth of THE, the influencing factors of THE and the extent of their influence also differ. Additionally, no standard approach exists for the measurement of the driving factors; thus, the selection and definition of those factors have inevitably been somewhat subjective and dependent on the data available. Therefore, scholars have often selected driving factors according to the characteristics or hot issues of the study area. Previous studies [8, 12] have employed instrumental variable quantile regression or generalized estimating equation methods for panel models to analyze THE, and other scholars [13, 14] have used logistic regression, boosted decision trees, neural networks, and the ARIMA model to predict THE. However, a common point is that the amount of data used is large and the calculations are complicated, providing no benefits for short-term analyses or situations where there is “poor information”.

Owing to China’s socialist system and large population, the results of previous studies have only reference significance and no decisive significance. In China, THE has grown considerably since economic reform started in 1978, and its growth rate has exceeded that of GDP [15]. This phenomenon has become more obvious in the 21st century, placing a heavy burden on the government and residents. In 2009, due to the excessive increase in medical expenses, the Chinese government began to implement the new health system reform, with one of the main tasks reducing the burden of medical treatment for residents and alleviating the “difficulty and high cost of getting medical treatment” [16]. However, THE and per capita health expenditure continued to increase rapidly—the average annual growth rate of THE in

2009-2018 was 14.45%, which was higher than the average annual growth rate of GDP (11.12%). The elasticity of health consumption during this period was 1.30; that is, for every 1% increase in GDP, THE increased by 1.30%, and THE accounted for 6.57% of GDP in 2018 [17]. Zhang et al. [9], experts from the China National Health Development Research Center, determined that the elasticity of health consumption is approximately 1.2, which can guarantee the economic sustainability of health financing. After analysis of historical changes in THE in China and reference to changes in health financing development trends and the proportion of THE in GDPs of the OECD countries, 8% of GDP was determined to be the upper limit or warning value of the sustainability of THE in China. However, the growth of THE has been rapid, and if this trend of excessive growth is not controlled in the future in China, it may exceed social and economic affordability, and the sustainability of health funding will not be guaranteed.

Over the first 19 years of the 21st century, not enough information has yet accumulated to analyze the driving factors of a country's THE and establish a predictive model. Additionally, the growth of health expenditure is affected by objective and subjective factors, the connotations and extensions are difficult to measure and the characteristics are neither obvious nor easy to analyze. However, Deng's gray system theory, especially the gray relational analysis and gray prediction model, can be used to model, analyze, monitor, and control uncertain systems and solve the problem of uncertain gray information. This theory has been widely used in both the economic [18], biological [19] and environmental fields [20], but few studies have applied it in the field of health. Therefore, the correlation analysis and the improved prediction model of gray system theory were employed in the field of health economics in this paper to analyze the main driving factors of the increase in China's THE since the beginning of the 21st century and establish a prediction model. At the same time, the traditional BP neural network model was used to determine the accuracy of the prediction model.

## 2 Methods

### *2.1 Gray Correlation Analysis*

Gray correlation analysis, which is used to evaluate the main driving factors of THE, measures the degree of correlation among factors in a system based on the similarity or dissimilarity of the development trends. The comparative analysis of factors in the system includes the geometric shapes of several curves, and when the shapes are approximate, the degree of correlation among the factors is significant and the degree of similarity among the objects considerable. Additionally, gray correlation analysis does not require many samples, the typical distribution rules are irrelevant in the analysis, and accurate knowledge of the system can be realized with partially known information [21].

The gray correlation analysis procedure is described in detail below. IBM SPSS Statistics (version 24.0) was used for the calculation.

**Step 1:** Determination of the reference sequence

Let $X_0$= {$X_0(k)$, $k$ = 1, 2… m} be original reference sequence that reflects THE in China in 2000-2018, and let $X_i$= {$X_i(k)$, $i$ = 1, 2…, n} be the original comparative sequence that reflects the driving factors, such as economy, population, health service utilization, and policies.

**Step 2:** Initialization process

First, the original sequence is interpreted by dimensionless processing to avoid the effect of unit inconsistency on the correlation analysis; this paper uses the mean value processing approach. The sequences processed by initialization are denoted $x'(k)$ and expressed as shown in Eqs. (1) and (2).

$$x_i'(k) = \frac{x_i(k)}{\bar{x_i}} \qquad \text{Eq. (1)}$$

$$\bar{x_i} = \frac{1}{m}\sum x_i(k) \qquad \text{Eq. (2).}$$

**Step 3:** Calculation of the gray correlation coefficients of each sequence

The calculation method of the gray correlation coefficient is shown in Eq. (3), where $\xi$ is the resolution coefficient (within the [0–1] interval; the value is usually 0.5), $\triangle_{max}$ is the maximum difference between two sequences, and $\triangle_{min}$ is the minimum difference.

$$\varepsilon_i(k)=\frac{\triangle_{min}+\xi*\triangle_{max}}{\triangle_i(k)+\xi*\triangle_{max})} \qquad \text{Eq. (3).}$$

**Step 4:** Determination of correlation grade

Finally, the value of the correlation degree is $\beta_i$, which is shown as Eq. (4), and the rank of the correlation degree among the driving factors is $\gamma_i$.

$$\beta_i=\frac{1}{m}\sum\varepsilon_i(k) \qquad \text{Eq. (4).}$$

## *2.2 Model of Gray Prediction*

### *2.2.1 Traditional Gray Model*

The theory of the gray system is that all random quantities are gray quantities and gray processes that vary within a certain range and a certain period of time and that no matter how complex the objective system is, it is always related, has overall functions and is therefore orderly. Therefore, when the gray system processes data, it is not seeking their statistical law and probability distribution, but rather to make them into more regular time series data after processing them in a certain way, namely, as a "module", and then builds a model. The module's geometric meaning refers to the general term of the continuous curve and its bottom (i.e., abscissa) given on the two-dimensional plane of time and data. A module composed of known data columns is called a white module, and a module that is extrapolated from the white module to the future, that is, a module composed of predicted values, is called a gray module. Specifically, the module seeks to find the inherent laws in the irregular original data through the gray generation function and the differential fitting method in the case of poor information. Additionally, the module requires a small number of experimental data (at least four) for accurate prediction and has low data distribution requirements [8]. The traditional gray models are divided into two types, namely, GM(1,1) and GM(1,N). GM(1,1) is a univariate prediction model, and it does not consider which factors will influence the development of the system [22-24]. GM(1,N) represents the first-order gray model that has *N* variables, including the total number of ($N$−1) independent variables and one dependent variable.

Suppose that there are a total of n variables denoted by $\mathrm{X_i}^{(0)}$ and that each variable has m original sequences, as presented in Eq. (5).

$$X_i^{(0)}(k) = \{x_i^{(0)}(1), x_i^{(0)}(2)\ldots, x_i^{(0)}(m)\} \qquad (i=1,2,\ldots, n;\ k=1,2,\ldots, m) \qquad \text{Eq. (5)}$$

**Step 1:** Accumulated generating operation (1-AGO)

First, the original sequences of each variable can be processed by using 1-AGO, and $X_i^{(1)}$ is the 1st-order AGO sequence of $X_i^{(0)}$. The method of 1-AGO and $X_i^{(1)}$ is shown in Eqs. (6) and (7).

$$x_i^{(1)}(k) = \textstyle\sum_1^k x_i^{(0)}(k) \qquad \text{Eq. (6)}$$

$$x_i^{(1)} = \{x_i^{(1)}(1), x_i^{(1)}(2), \cdots, x_i^{(1)}(m)\} \qquad \text{Eq. (7)}$$

**Step 2:** Determining the driving parameters

Eq. (8) is the whitening differential equation of the GM(1,N) model.

$$\frac{dx_1^{(1)}(k)}{dt} + a x_1^{(1)}(k) = \textstyle\sum_2^n b_{i-1} x_i^{(1)}(k) \qquad (k=2,3,\ldots, m) \qquad \text{Eq. (8)}$$

Then, the gray differential equation can be obtained, as presented in Eq. (9).

$$x_1^{(0)}(k) + a z_1^{(1)}(k) = \textstyle\sum_2^n b_{i-1} x_i^{(1)}(k) \qquad \text{Eq. (9)}$$

where $z_1^{(1)}(k)$ is defined as shown in Eq. (10)

$$z_1^{(1)}(k) = \tfrac{1}{2}[x_1^{(1)}(k) + x_1^{(1)}(k-1)] \qquad (k=2,3,\ldots, m) \qquad \text{Eq. (10)}$$

where a represents the system development parameter and $b_i$ represents the driving parameter.

Then, $Y$, $B$, and $\beta$ are defined as shown in Eq. (11), where $Y = B * \beta$.

$$Y = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{bmatrix} \quad B = \begin{bmatrix} z_2^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_n^{(1)}(2) \\ z_2^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_n^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ z_2^{(1)}(m) & x_2^{(1)}(m) & \cdots & x_n^{(1)}(m) \end{bmatrix}$$

$$\beta = \begin{bmatrix} a \\ b_1 \\ b_2 \\ \vdots \\ b_{n-1} \end{bmatrix} \qquad \text{Eq. (11)}$$

In the GM(1,N) models, $Y$ and $B$ are known quantities, and $\beta$ is the pending parameter. The gray parameter, $P_N$, represents the vector composed of the system development parameter, and the driving parameters can be obtained according to the least-squares method according to Eq. (12).

$$\hat{\beta} = (B^T B)^{-1} B^T Y = \begin{bmatrix} \hat{a} \\ \hat{b}_1 \\ \vdots \\ \hat{b}_{n-1} \end{bmatrix} \qquad \text{Eq. (12)}$$

**Step 3:** Prediction by using the inverse accumulated generating operation

Then, the solution of the equation can be obtained by substituting the gray parameter in Eq. (8), as presented in Eq. (13), which is called the time-corresponding formula of GM(1,N).

$$\hat{x}_1^{(1)}(k+1) = \left[ x_1^{(0)}(1) - \frac{1}{\hat{a}} \sum_{i=2}^{n} \hat{b}_{i-1} \hat{x}_i^{(1)}(k+1) \right] e^{-\hat{a}k} + \frac{1}{\hat{a}} \sum_{i=2}^{n} \hat{b}_{i-1} x_i^{(1)}(k+1)$$

Eq. (13)

Finally, the $k+1$-th predictive value can be obtained, $\hat{x}_1^{(0)}(k+1)$, through the inverse accumulated generating operation, as presented in Eq. (14), which is called the accumulative subtraction formula of GM(1,N).

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k) \qquad \text{Eq. (14)}$$

*2.2.2 New Structure of the Multivariate Gray Prediction Model*

The premise of the GM(1,N) model is fairly good because the system is whitened by many effective messages around its forecast origin. However, many scholars have noted some flaws in the existing GM(1,N) model's prediction ability [25-27]. Zeng et al. [28], experts in gray prediction theory, pointed out three major defects in the traditional multivariate gray prediction model GM(1,N), that is, the mechanism defects caused by the over-idealization of the derivation process, the parameter defects caused by the "nonhomology" of parameter estimation and the application object, and the structural defects of lack of data mining and equivalent substitution[28]. These are all important issues that affect the accuracy of the prediction model. They revised the GM(1,N) model in view of the defects and proposed a new structure of the multivariate gray prediction model, namely, NSGM(1,N), and the calculation method is as follows. The formulas and methods that are the same as those in GM(1,N) will not be repeated.

**Step 1:** Definition of the NSGM(1,N) model

Consistent with the traditional gray prediction model GM(1,N), $X_i^{(0)}(k)$、$x_i^{(1)}(k)$ and $z_1^{(1)}(k)$ are defined in the same way, but the model definition of NSGM(1,N) is different, as shown below in Eq. (15).

$$x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_2^n b_i x_i^{(1)}(k) + h_1(k-1) + h_2 \quad \text{Eq. (15)}$$

It is defined as a new gray model structure with a first-order equation and multiple variables, referred to as NSGM(1,N). The formula also contains system development parameters (a) and driving parameters (bi). At the same time, h1(k-1) is defined as the linear correction term of the model, h2 is defined as the gray action, and the parameter is listed as $\hat{p}$=[b2,b3,b4⋯bn,a,h1,h2]. Therefore, the first-order model is shown as Eq. (16).

$$\hat{x}_1^{(0)}(k) = \sum_2^n b_i \hat{x}_1^{(1)}(k) - a z_1^{(1)}(k) + h_1(k\text{-}1) + h_2 \qquad \text{Eq. (16)}$$

**Step 2:** Parameter estimation of the NSGM(1,N) model

The least-squares method was also used to solve the parameter $\hat{p}$ in the NSGM(1,N) model, as shown in Eq. (17) and Eq. (18).

$$\hat{p} = (B^T B)^{-1} B^T Y \qquad \text{Eq. (17)}$$

$$Y = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{bmatrix} \; B = \begin{bmatrix} x_2^{(1)}(2) & x_3^{(1)}(2) & \cdots & x_N^{(1)}(2) & -z_1^{(1)}(2) & 1 & 1 \\ x_2^{(1)}(3) & x_3^{(1)}(3) & \cdots & x_N^{(1)}(3) & x_2^{(1)}(3) & 2 & 1 \\ & \vdots & & & \vdots & \vdots & \vdots \\ x_2^{(1)}(m) & x_3^{(1)}(m) & \cdots & x_N^{(1)}(m) & x_2^{(1)}(m) & m-1 & 1 \end{bmatrix} \qquad \text{Eq. (18).}$$

**Step 3:** Time-corresponding formula and accumulative subtraction formula of the NSGM(1,N) model

Eq. (8) is used to derive the time-response formula in the GM(1,N) model. However, the parameters estimated by Eq. (9) are used as the parameters of the time-response function, which leads to the "nonhomology" of parameter estimation and the application object. The NSGM(1,N) model uses one first-order equation, which is an equivalent modification of Eq. (15), to derive the time response of NSGM(1,N), which ensures parameter estimation "homology" with parameter application. Therefore, the time-response formula is shown as Eq. (19).

$$\hat{x}_1^{(1)}(k) = \sum_{t=1}^{k-1}\left[\mu_1 \sum_{i=2}^{N} \mu_2^{t-1}\, b_i x_i^{(1)}(k-t+1)\right] + \ \mu_2^{k-1}\hat{x}_1^{(1)}(1) \ + \ \sum_{j=0}^{k-2}\left[\mu_2^{j}(k-j)\mu_3 + \mu_4\right] \qquad (k=2,3,4,\ldots.,m) \qquad \text{Eq. (19)}$$

The accumulative subtraction formula of NSGM(1,N) is shown as Eq. (20).

$$\hat{x}_1^{(0)}(k) = \mu_1(\mu_2-1)\sum_{t=1}^{k-2}\left[\sum_{i=2}^{N} \mu_2^{t-1}\, b_i x_i^{(1)}(k-t)\right] + \ \mu_1 \sum_{i=2}^{N} b_i\, x_i^{1}(k) + \sum_{j=0}^{k-3} \mu_2^{j}\mu_3 + (\mu_2-1)\mu_2^{k-2}x_1^{(1)} \ + \mu_2^{k-2}(2\mu_3+\mu_4) \qquad (k=2,3,4,\ldots.,m) \qquad \text{Eq. (20)}$$

where

$\mu_1=\frac{1}{1+0.5a}$ $\quad \mu_2=\frac{1-0.5a}{1+0.5a}$ $\quad \mu_3=\frac{h_1}{1+0.5a}$ $\quad \mu_4=\frac{h_2-h_1}{1+0.5a}$.

## 3 Data Collection

As mentioned above, the characteristics of each country are different, so the study of Chinese health expenditure cannot completely adopt the variables used by other scholars, although we explored the research in other parts of the world. At the same time, we identified the popular topics of Chinese scholars' research regarding China's medical and health system reform. To a certain extent, the more influencing factors are selected, the more accurate the description and prediction of health expenditure will be. The model needs to be not only accurate but also concise, so we selected only representative variables from the popular topics. Finally, we selected 9 representative factors, including factors in the fields of economy, population, health institutions, and public policy. These data come from the China Statistical Yearbook and China National Health Accounts Report, and the driving factors are described below.

### *3.1 Demographics*

After the availability of data, practical possibilities and interrelationships among the factors were considered, the demographic factors selected for this paper were population growth and aging. The growth of the population has increased the number of potential users of medical services, which will definitely effect change in THE. Additionally, not only the size but also the age structure of the population are critical factors that affect THE. With the increase in average life expectancy and the decrease in birth and death rates, the number and proportion of the elderly population continue to increase, and the problem of aging populations has intensified throughout the world. Aging is also associated with higher risks of chronic diseases, mild disability, cognitive decline, etc. [29]. The prevalence of multimorbidity increases substantially with age and is present in most people aged 65 years and older [30]. In China, by the end of 2018, the number of citizens aged 65 and over had reached nearly 167 million, accounting for 11.94% of the total population, and the increase in elderly people in China has increased the burden on society in terms of chronic diseases contracted by the elderly [31]. A WHO study [32] showed that between 2020 and 2030, the number of elderly individuals suffering from one or more chronic diseases in China is projected to increase by at least 40%, and the proportion of the elderly population will reach 28% by 2040. Therefore, with the increased elderly population, the challenges for medical services and social policy will increase. Scholars [7, 33, 34] worldwide have investigated the aging of the population as an important driving factor when researching changes in THE. Therefore, the population and the number of people aged 65 years and over were selected as population factors in relation to the change in THE.

### *3.2 Economy*

The relationship between GDP and THE is a popular topic in many studies on health economics [35, 36]. GDP is an overall economic indicator that measures a country's total income and can reflect its economic strength; the proportion of THE in GDP is an important indicator of a country's health input. As China's economic strength has increased, the living standards of residents have also continuously improved. The level of national living standards depends on the level of consumption. If residents do not consume or have no money to consume, they cannot benefit from economic growth, and national economic growth will lose its meaning. At the same time, consumption is an important behavior and process in human social and economic activities because it is not only the end point but also the starting point of economic activities. Therefore, household consumption expenditure plays a decisive and vital role in the national standard of living and national economy.

### *3.3 Public Policy*

Policies, including medical, medical insurance, and drug policies, are very complex and difficult to analyze, so a comprehensive analysis of the impact of various policies on health expenditure is difficult to achieve. However, standardizing financing and compensation mechanisms, improving the health of the population, and sharing the economic risks of disease are the ultimate goals of various policies. Therefore, indicators of the results of health policies were chosen to reflect the relationship between health policies and health expenditure, which is more intuitive and easier to understand. First, according to the International Classification for Health (ICHA), general government health expenditure (GGHE) reflects the role played by governments at all levels and social security funds as fundraisers. The government can affect a country's health sectors, and subsequently its health outcomes, in several ways, such as the provision of public health services and coverage of medical services [37]. Moreover, under the Chinese medical and health system, the government plays an irreplaceable leading role in the health service market, providing public goods, improving income distribution, and promoting social equity, so its health investment deeply reflects its emphasis on healthcare and livelihood issues, such as residents' health and medical burden. Additionally, the social medical security fund has an impact on health service utilization and expenditure [38] that reflects the contribution of various social medical security systems, such as urban and rural medical insurance, urban workers' medical insurance, new rural cooperative medical insurance and enterprise employee medical and health expenses. At the same time, the new medical reform policies also focus on clarifying government responsibilities and establishing a scientific and effective medical insurance system, so GGHE was selected in this paper to reflect the role of the government and social security departments in the health field. Second, out-of-pocket expenditure (OOP) was selected to reflect the economic burden of residents, that is, the cash payment residents must make when receiving various medical and health services, which is also a component of private expenditure on health (PHE) in the ICHA. The size of OOP also affects residents' access to and choice of medical and health services. Finally, infant mortality (INF) is an important indicator of a country's health that is associated with a variety of factors, such as maternal health, quality of service, access to medical care, socioeconomic conditions, and public health practices [39-41]. Therefore, it was selected to reflect the national health situation.

### *3.4 Health Institutions*

The development of health institutions has improved accessibility from the perspective of providers of health services, affecting the provision and utilization of health services. The number of beds and health technicians, which are important indicators of the size of the institution, were selected to reflect the impact of the development of medical institutions on THE.

## 4 Results

### *4.1 Description of Total Health Expenditure and Main Driving Factors*

The description of THE and main driving factors for 2000-2018 are shown in and Fig. 1. In China in 2000, THE was 458.66 billion yuan, accounting for 4.57% of GDP, and by 2018, THE was 5,912.19 billion yuan, accounting for 6.57% of GDP. From 2000 to 2018, THE increased by 1,189.01%, with an average annual growth rate of 15.26%, much higher than the

GDP annual average growth rate of 12.97% in the same period. At the same time, GGHE grew rapidly, with the proportion of THE rising from 38.38% to 53.82%, while the OOP proportion of THE gradually decreased from 58.98% to 28.61%, which was very close to the target of 28% set in China's 13th five-year (2016-2020) health and wellness plan. Moreover, residents' consumption and living standards were constantly improving, and HCE was increasing from year to year, with an average annual growth of 11.16%. In terms of demographic factors, China's population was gradually increasing, but the natural population growth rate was decreasing. ABOVE65 showed an upward trend that reached 11.94% in 2018, indicating that the aging of Chinese society was serious. In terms of health institutions, PRE and BED were constantly increasing; in 2018, they increased by 112.19% and 164.53% compared with 2000, and the average annual growth rates were 4.27% and 5.55%, respectively.

***4.2 Results of the Main Driving Factor Analysis***

The degree of correlation between GGHE and the change in THE was 0.941, ranking 1$^{st}$ among all the factors, suggesting that GGHE was the factor most closely related to the change in THE. This finding indicated that on the one hand, the government plays a leading role in the health industry and has a critical impact on the development of health services and on the other hand, through the implementation and improvement of social insurance policies, the government has enabled social medical insurance funds to play a vital role in ensuring the health of the population. Among other health policy factors, the degree of correlation between OOP and THE was 0.878, ranking 4$^{th}$, suggesting that changes in the proportion of residents' OOP will also have a great impact on changes in THE.

The degrees of correlation between GDP and THE and between HCE and THE were 0.910 and 0.904 and the correlation grades 2$^{nd}$ and 3$^{rd}$, respectively, indicating that the development of China's economy and the increase in residents' income are closely related to improvements in health.

Additionally, the results show that the degrees of correlation between BED and THE and between PRE and THE were 0.791 and 0.756, respectively, indicating that the development of the economy has caused the development of health institutions and that the availability of health services is also increasing, which promotes the provision and utilization of health care services and has an important impact on THE.

Additionally, the correlation degree between ABOVE65 and THE was 0.723, proving that the aging of the population was an important driving factor affecting THE, whereas the correlation degree between POP and THE was 0.672.

Last, the degree of correlation between INF and THE was below 0.6, at only 0.573, indicating that INF had less impact on THE than other factors.

### ***4.3 Prediction Model of Total Health Expenditure***

To evaluate the prediction accuracy of the model, all the experimental data were divided into two parts: training (2000-2016) and test data (2017 and 2018). The training data were used for the training of the model, and the test data were used to evaluate the predictive potential of the NSGM(1,10) model.

First, all 10 variables were included in the model to establish NSGM(1,10), including THE as the dependent variable and the 9 driving factors as independent variables.

When the MATLAB processing codes of NSGM(1,10) are run, the gray parameter can be obtained as shown in Eq. (20).

$$\hat{\beta}=(b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, a, h_1, h_2)^T$$

$$= (-10.4199,17.9940,\ 0.0430,0.0428,\ 0.5213,1.9117,0.5433,0.1432,22.3902,0.6942,\ 21536.5233,\ 20977.0284) \qquad \text{Eq. (20)}$$

Table 2 shows the results of using NSGM(1,10) to compare the prediction of THE with the actual data. The residual percentage of the training data (2000-2016) is within 1%, except for 2004 and 2007, where it is slightly higher than 1%, and the average residual percentage of the training data is 0.36%. Additionally, the residual percentages of prediction and actual data of the test data (2017-2018) are 1.36% and 2.34%, respectively, and the average residual percentage is only 1.85%. Thus, the NSGM(1,10) model has good fit and predictive ability.

To verify the superiority of the prediction results of the NSGM(1,10) model, this paper also used the traditional gray prediction models, GM(1,1) and GM(1,N), to fit and predict the data.

When the MATLAB processing codes of GM(1,1) are run, the gray parameter is calculated as a=-0.147532 and b=430.168721. The results shown in Table 2 indicate that the residual percentage in 2004-2007 is more than 10%, while the residual percentage in 2009 and 2013 is within 1%, and the average residual percentage of the training data is 6.06%. Thus, the fit of GM(1,1) for the training data (2000-2016) is poor and unstable. Moreover, the residual percentages of the prediction and actual data of the test data (2017-2018) are 8.07% and 11.43%, respectively, and the average residual percentage is 9.75%, which is close to 10%, so there is a large gap between the prediction and the actual data.

Then, by following the procedures of GM(1,10), the gray parameter was calculated as

$$\hat{\beta}=(a, b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9)^T$$

$$=(0.9170,85.818,80,035,0.011,0.009,0.506,0.963,2.522,0.570,8.825) \quad \text{Eq. (21).}$$

Table 1 shows the results of using GM(1,10) to compare the prediction of THE with the actual data. The residual percentages of the training data (2000-2016) are relatively large, even exceeding 20% in 2002-2003, and the average residual percentage of the training data is 10.97%, which is the largest among the three methods. For the test data (2017-2018), the residual percentages of the prediction and actual data are 10.97% and 6.82%, respectively, and the average residual percentage is 6.82%, which is better than the test results of GM(1,1).

Finally, to show the advantage of the gray model for predicting THE with scanty data, we also used the BP neural network, which is widely used in the field of prediction, to predict THE. As in NSGM(1,N), we used 2017-2018 data as test data to evaluate the prediction accuracy of the model. MATLAB was used to perform the BP neural network model, and the final model contained a two-layer feedforward network. There were six TANSIG hidden neurons in the hidden layer and one PRRELIN neuron in the output layer, and the TRAINLM network training function was used.

Finally, after many simulation trainings, we selected the 10 best results, which are listed in Table 3. The results show that there are great differences among the 10 results. The minimum residual percentage of the training data is 0.245%, and the maximum is 5.628%. At the same time, the minimum residual percentage of the test data is 1.504%, and the maximum is 9.093%. The average residual percentages of the 10 results of the training data and the test data are 1.140% and 2.930%, respectively, and we also reach a good level of fit and prediction. Although the minimum residual percentage of the training data and test data is smaller than in the results of NSGM(1,10), the results of NSGM(1,10) are better than the 10-time average of the BP neural network model.

The comparison among the predictions of the four predictive methods and the actual data are shown in Fig. 2, which indicates that the curve of NSGM(1,N) is closest to the actual data.

## 5 Discussion

This paper uses data from 2000-2018 to analyze the main driving factors of the growth in THE by using data from China. Additionally, it explores the application value of gray prediction theory in health expenditure prediction, which is crucial for the formulation of effective, strategic, and health service policies to facilitate the progress of China’s new health system reform.

The types and degrees of driving factors are different in different countries, as mentioned in the introduction, and there are subjective, objective, and data-available factors in the selection of influencing factors. Therefore, this paper selects 9 hot-topic factors in health areas to explore their relationships with THE and uses these 9 factors to establish and test the THE prediction model. The results of the predicted model are excellent, which proves that these 9 factors have good representativeness and largely reflect the trend of THE.

In public policy and health institutions, the government and society have played a positive role in improving health conditions and reducing the economic burden. When the government proposed a new health system reform in China in 2009, it needed to increase the input of government in all fields, accelerate the establishment and improvement of a multilevel medical security system covering urban and rural residents, and improve the primary health service system to promote fairness and efficiency in the medical and health industry [16]. In our research results, THE is highly correlated with general government expenditure on health and is also strongly related to the development of health institutions, which shows that through the formulation of policies, the government and society have invested heavily in health care and health institution construction, and this investment has played a vital role in improving the fairness and efficiency of the health care system. Therefore, the proportion of OOP has shown a downward trend year by year, which is gradually approaching the goal set by China's 13th five-year (2016-2020) health and wellness plan (28%), whereas the OOP health expenditure is still increasing rapidly, and the medical burden of residents has not been substantially alleviated. Therefore, improving the allocation efficiency of government health expenditure, perfecting the medical insurance system [42] and increasing society's role in sharing the risk of heath expenditure are valuable in controlling the growth of THE and reducing residents' medical burden.

In terms of demographics and the economy, aging is a major concern. The population is aging rapidly as a result of the baby boom, the One Child Policy and the declining mortality rate, and the demographic household structure is gradually becoming a "4–2-1" or "4–2-2" formula [43], meaning the elderly population will continue to increase. Moreover, this paper demonstrates that aging is closely related to the growth in total health expenditure, which is consistent with other research results [25-27]. Therefore, this paper proposes that aging provides more opportunities for the increase in THE and is a carrier that can combine the improvement of the economy, medical insurance, and medical science with the health of the population and convert them to health expenditure. Therefore, in the context of the increasing number of older people, there is an urgent need to pay more attention to the health of the elderly, develop strategies for preventive and rehabilitative care, particularly in medical treatment and nursing of the elderly, and formulate corresponding insurance strategies to reduce the medical burden of the elderly. Moreover, health literacy is inversely proportional to the utilization of and expenditure on healthcare [44]. Therefore, it is necessary to adopt health education and knowledge popularization measures to improve the health literacy of the population, including elderly and young people, to control health expenditure. At the same time, measures such as providing regular physical examinations and improving sanitation facilities for the population can be used to transform the fruits of economic development into health improvements for elderly and young people.

Compared with the traditional gray prediction models, GM(1,1) and GM(1,N), the improved NSGM(1,N) model not only avoids the problems of the GM(1,N) model but also improves the predictive accuracy. The residual prediction of the NSGM(1,N) model is smaller than that of the BP neural network, so the predictability is better; however, the predictions of the BP neural network were different and varied greatly in each run of the code, whereas the predictions of GM(1,N) were certain when the training data were determined, so GM(1,N) has better prediction stability. Finally, the BP neural network model is suitable for the prediction of more data because the model was established only in terms of fewer data, the predicted simulation sequence for the training data was very close to the original sequence, and the residual percentage is small. We conclude that the improved NSGM(1,N) model can predict health expenditure fairly accurately in the situation of poor information, with results superior to those of the traditional gray model and BP neural network model. Therefore, the NSGM(1,N) gray prediction model has good applicability in predicting THE.

Our analysis has two main limitations. First, although the 9 factors we selected were well-represented and the predictive model was accurate, they were limited and could not fully explain the increase in total health expenditure. Second, there are great differences in the economies, populations and policies of different regions in China, and this article can only reflect the overall situation in China rather than the situation in a certain region.

## 6 Conclusion

Given this study’s analysis, the following conclusions can be drawn. First, under the socialist system, the policies and investment of the Chinese government and society have played a crucial role in reducing the burden on people. In addition, China's medical system reform has been effective, and the proportion of OOP has gradually decreased from year to year. To a certain extent, residents’ medical burden has been reduced. Second, the improvement of the economy and the aging of the population, which are closely related to THE, have increased the demand for health services, leading to continuous increases in THE, so improving the efficiency of investment and providing preventive health care and nursing for the elderly are crucial. Third, the improved NSGM(1,N) model achieves good prediction accuracy as it has unique advantages in simulating and predicting THE; thus, it can provide a basis for policy formulation.

## List of abbreviations

THE: Total Health Expenditure; NSGM: Multivariate Gray Prediction Model; GM: Gray Model; GDP: Gross Domestic Product; ARIMA: Autoregressive Integrated Moving Average Model; OECD: Organization for Economic Co-operation and Development; AGO: Accumulated Generating Operation; ABOVE65: Number of People Aged 65 and Over; POP: Population; PER Number of Medical Technical Personnel; BED: Number of Beds in Health Care Institutions; GGHE: General Government Health Expenditure; OOP: Out-of-pocket Health Expenditure; INF: Infant Mortality; HCE: Household consumption expenditure; ICHA:

International Classification for Health; PHE: private expenditure on health; BP: Back Propagation.

## Declarations

### *Ethics Approval and Consent to Participate*

Not applicable.

### *Consent for Publication*

Not applicable.

### *Availability of Data and Materials*

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

### *Competing Interests*

The authors declare that they have no competing interests


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### *Authors' Contributions*

All coauthors have contributed to the development of the study design, conduction of analysis, interpretation of results and writing of the manuscript., and approved the publication.

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**Table 1** The description of THE and main driving factors for 2000-2018.

| YEAR | THE[a] | ABOVE65[b] | POP[c] | GDP[d] | PER[e] | BED[f] | GGHE[g] | OOP[h] | INF[i] | HCEj |
|---|---|---|---|---|---|---|---|---|---|---|
| 2000 | 458.66 | 88.21 | 1267.43 | 10028.01 | 4490.80 | 3177.00 | 175.591 | 270.517 | 32.2 | 3721 |
| 2001 | 502.59 | 90.62 | 1276.27 | 11086.31 | 4508.00 | 3201.00 | 178.78 | 301.388 | 30 | 3987 |
| 2002 | 579.00 | 93.77 | 1284.53 | 12171.74 | 4270.00 | 3136.00 | 207.478 | 334.214 | 29.2 | 4301 |
| 2003 | 658.41 | 96.92 | 1292.27 | 13742.20 | 4381.00 | 3164.00 | 238.514 | 367.867 | 25.5 | 4606 |
| 2004 | 759.03 | 98.57 | 1299.88 | 16184.02 | 4486.00 | 3268.00 | 288.23 | 407.135 | 21.5 | 5138 |
| 2005 | 865.99 | 100.55 | 1307.56 | 18731.89 | 4564.05 | 3367.50 | 335.713 | 452.097 | 19 | 5771 |
| 2006 | 984.33 | 104.19 | 1314.48 | 21943.85 | 4728.35 | 3511.80 | 400.17 | 485.356 | 17.2 | 6416 |
| 2007 | 1157.40 | 106.36 | 1321.29 | 27009.23 | 4913.19 | 3701.10 | 543.166 | 509.866 | 15.3 | 7572 |
| 2008 | 1453.54 | 109.56 | 1328.02 | 31924.46 | 5174.48 | 4038.70 | 726.035 | 587.586 | 14.9 | 8707 |
| 2009 | 1754.19 | 113.07 | 1334.50 | 34851.77 | 5535.12 | 4416.60 | 920.92 | 657.116 | 13.80 | 9514.00 |
| 2010 | 1998.04 | 118.94 | 1340.91 | 41211.93 | 5876.16 | 4786.80 | 1085.16 | 705.129 | 13.10 | 10919.00 |
| 2011 | 2434.59 | 122.88 | 1347.35 | 48794.02 | 6202.86 | 5159.90 | 1360.70 | 846.528 | 12.10 | 13134.00 |
| 2012 | 2811.90 | 127.14 | 1354.04 | 53858.00 | 6675.55 | 5724.80 | 1573.43 | 965.632 | 10.30 | 14699.00 |
| 2013 | 3166.90 | 131.61 | 1360.72 | 59296.32 | 7210.58 | 6181.90 | 1767.35 | 1072.934 | 9.50 | 16190.00 |
| 2014 | 3531.24 | 137.55 | 1367.82 | 64128.06 | 7589.79 | 6601.20 | 1969.96 | 1129.541 | 8.90 | 17778.00 |
| 2015 | 4097.46 | 143.86 | 1374.62 | 68599.29 | 8007.54 | 7015.20 | 2299.99 | 1199.265 | 8.10 | 19397.00 |
| 2016 | 4634.49 | 150.03 | 1382.71 | 74006.08 | 8454.40 | 7410.50 | 2502.69 | 1333.79 | 7.50 | 21285.00 |
| 2017 | 5259.83 | 158.31 | 1390.08 | 82075.43 | 8988.23 | 7940.30 | 2850.49 | 1513.36 | 6.80 | 22935.00 |
| 2018 | 5912.19 | 166.58 | 1395.38 | 90030.95 | 9529.18 | 8404.10 | 3182.16 | 1691.20 | 6.10 | 25002.00 |

a Total Health expenditure (billion); b Number of people aged 65 and over (million); c Population (million); d Gross domestic product (billion); e Number of medical technical personnel (thousand); f Number of beds in health care institutions (thousand); g General government expenditure on health (billion); h Out-of-pocket health expenditure (billion); i Infant mortality rate (‰); j Household consumption expenditure (yuan).

**Table 2** Comparison of the actual data and prediction by the gray prediction model

| Year | Actual data | GM(1,1) | | GM(1,10) | | NSGM(1,10) | |
|---|---|---|---|---|---|---|---|
| | | Prediction | $\phi_i$[d] | Prediction | $\phi_i$ | Prediction | $\phi_i$ |
| 2000 | 458.66 | 458.66 | - | 458.66 | - | 458.66 | - |
| 2001 | 502.59 | 536.43 | 6.73 | 481.02 | 4.29 | 502.23 | 0.07 |
| 2002 | 579.00 | 621.71 | 7.38 | 713.56 | 23.24 | 578.52 | 0.08 |
| 2003 | 658.41 | 720.55 | 9.44 | 797.19 | 21.08 | 663.27 | 0.74 |
| 2004 | 759.03 | 835.09 | 10.02 | 869.58 | 14.56 | 751.09 | 1.05 |
| 2005 | 865.99 | 967.85 | 11.76 | 990.47 | 14.37 | 871.22 | 0.60 |
| 2006 | 984.33 | 1121.70 | 13.96 | 1050.55 | 6.73 | 979.24 | 0.52 |
| 2007 | 1157.40 | 1300.00 | 12.32 | 1308.47 | 13.05 | 1170.07 | 1.09 |
| 2008 | 1453.54 | 1506.70 | 3.66 | 1587.91 | 9.24 | 1439.62 | 0.96 |
| 2009 | 1754.19 | 1746.20 | 0.46 | 1932.70 | 10.18 | 1759.01 | 0.27 |
| 2010 | 1998.04 | 2023.80 | 1.29 | 2159.12 | 8.06 | 1996.37 | 0.08 |
| 2011 | 2434.59 | 2345.50 | 3.66 | 2707.82 | 11.22 | 2437.18 | 0.11 |
| 2012 | 2811.90 | 2718.40 | 3.33 | 3017.02 | 7.29 | 2812.44 | 0.02 |
| 2013 | 3166.90 | 3150.60 | 0.51 | 3384.96 | 6.89 | 3164.62 | 0.07 |
| 2014 | 3531.24 | 3651.40 | 3.40 | 3740.85 | 5.94 | 3533.78 | 0.07 |
| 2015 | 4097.46 | 4231.90 | 3.28 | 4441.08 | 8.39 | 4095.74 | 0.04 |
| 2016 | 4634.49 | 4904.60 | 5.83 | 4942.22 | 6.64 | 4634.52 | 0.00 |
| **$RE_1$ (%)[a]** | | | **6.06** | | **10.97** | | **0.36** |
| 2017[b] | 5259.83 | 5684.3 | 8.07 | 5650.81 | 7.43 | 5188.14 | 1.36 |
| 2018[b] | 5912.19 | 6587.9 | 11.43 | 6289.61 | 6.38 | 5774.04 | 2.34 |
| **$RE_2$(%)[c]** | | | **9.75** | | **6.82** | | **1.85** |

a The average residual percentage of training data

b Data used for testing

c The average residual percentage of test data.

d $\phi_i = \frac{|\text{Actual data} - \text{Prediction}|}{\text{Actual data}} x100\%$

**Table 3** Residual percentage of 10 predictions by the BP neural network (%)

| Year | Time | | | | | | | | | | Mean[d] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
| 2000 | 13.204 | 0.686 | 19.718 | 1.357 | 4.493 | 1.275 | 6.789 | 0.428 | 7.081 | 13.204 | 5.447 |
| 2001 | 8.942 | 1.216 | 17.543 | 0.816 | 1.578 | 0.549 | 6.228 | 0.224 | 3.232 | 8.942 | 4.259 |
| 2002 | 6.059 | 0.360 | 15.047 | 0.750 | 2.074 | 0.100 | 3.195 | 0.150 | 3.236 | 6.059 | 2.519 |
| 2003 | 2.757 | 0.780 | 11.839 | 0.290 | 1.332 | 0.053 | 4.390 | 0.133 | 1.651 | 2.757 | 1.808 |
| 2004 | 0.780 | 0.426 | 9.497 | 0.127 | 1.650 | 0.434 | 4.090 | 0.291 | 0.021 | 0.780 | 1.282 |
| 2005 | 0.150 | 0.007 | 7.105 | 0.127 | 1.871 | 0.420 | 3.557 | 0.161 | 0.674 | 0.150 | 0.744 |
| 2006 | 0.224 | 0.113 | 4.757 | 0.020 | 0.475 | 0.327 | 5.138 | 0.029 | 1.071 | 0.224 | 0.984 |
| 2007 | 0.412 | 0.971 | 2.742 | 0.202 | 0.878 | 0.329 | 6.645 | 0.227 | 3.584 | 0.412 | 0.432 |
| 2008 | 0.437 | 0.035 | 0.866 | 0.017 | 1.039 | 0.021 | 1.626 | 0.487 | 0.009 | 0.437 | 0.016 |
| 2009 | 0.382 | 0.048 | 0.304 | 0.090 | 0.727 | 0.464 | 0.182 | 0.482 | 1.968 | 0.382 | 0.048 |
| 2010 | 0.133 | 0.232 | 1.227 | 0.079 | 0.682 | 0.868 | 1.850 | 0.291 | 3.385 | 0.133 | 0.395 |
| 2011 | 0.096 | 0.086 | 1.362 | 0.031 | 0.305 | 1.073 | 1.628 | 0.442 | 0.163 | 0.096 | 0.195 |
| 2012 | 0.169 | 0.063 | 1.311 | 0.069 | 0.621 | 1.321 | 1.251 | 0.474 | 2.980 | 0.169 | 0.152 |
| 2013 | 0.210 | 0.804 | 0.929 | 0.093 | 0.800 | 1.262 | 2.189 | 0.242 | 2.632 | 0.210 | 0.144 |
| 2014 | 0.234 | 0.728 | 0.645 | 0.057 | 1.665 | 1.003 | 2.289 | 0.922 | 1.948 | 0.234 | 0.180 |
| 2015 | 0.181 | 1.351 | 0.454 | 0.008 | 2.819 | 0.393 | 2.300 | 1.195 | 1.095 | 0.181 | 0.166 |
| 2016 | 0.150 | 1.176 | 0.335 | 0.036 | 2.902 | 0.078 | 1.115 | 0.916 | 2.212 | 0.150 | 0.608 |
| **$RE_1$[a]** | **2.031** | **0.534** | **5.628** | **0.245** | **1.524** | **0.586** | **3.204** | **0.417** | **2.173** | **2.031** | **1.140** |
| 2017[b] | 3.107 | 0.524 | 1.505 | 1.377 | 5.847 | 2.816 | 1.578 | 3.370 | 8.322 | 3.107 | 4.890 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2018[b] | 1.301 | 3.324 | 7.346 | 1.632 | 12.339 | 4.132 | 6.046 | 9.962 | 16.432 | 1.301 | 0.969 |
| **$RE_2$[c]** | **2.204** | **1.924** | **4.426** | **1.504** | **9.093** | **3.474** | **3.812** | **6.666** | **12.377** | **2.204** | **2.930** |
| MSE | 0.00010 | 0.00010 | 0.00063 | 0.00000 | 0.00051 | 0.00008 | 0.00056 | 0.00008 | 0.00055 | 0.00010 | - |

a The average of the residual percentage of training data.

b Data used for testing.

c The average of the residual percentage of test data.

d The residual percentage of the mean of the 10 predictions.

## Figure legends

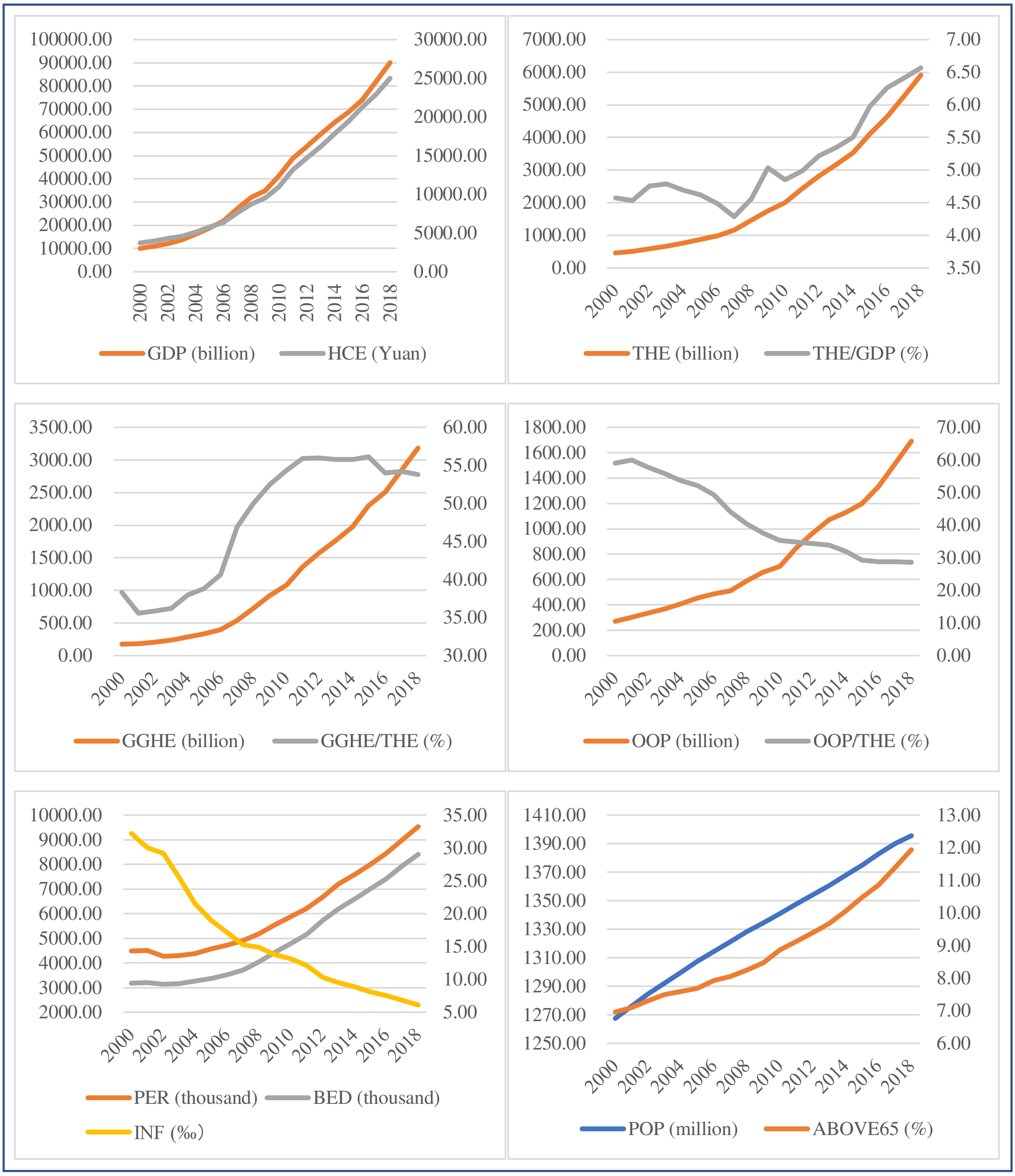


**Fig. 1** Description of total health expenditure and main driving factors

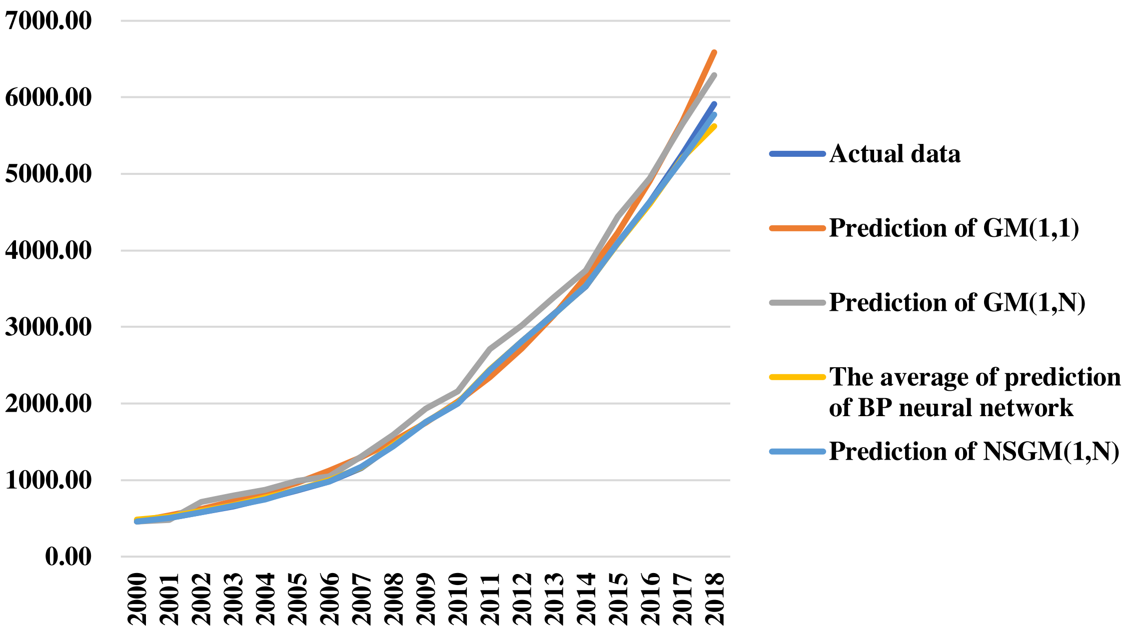


**Fig. 2** The similarity between the predictions and the actual data.

# Figures

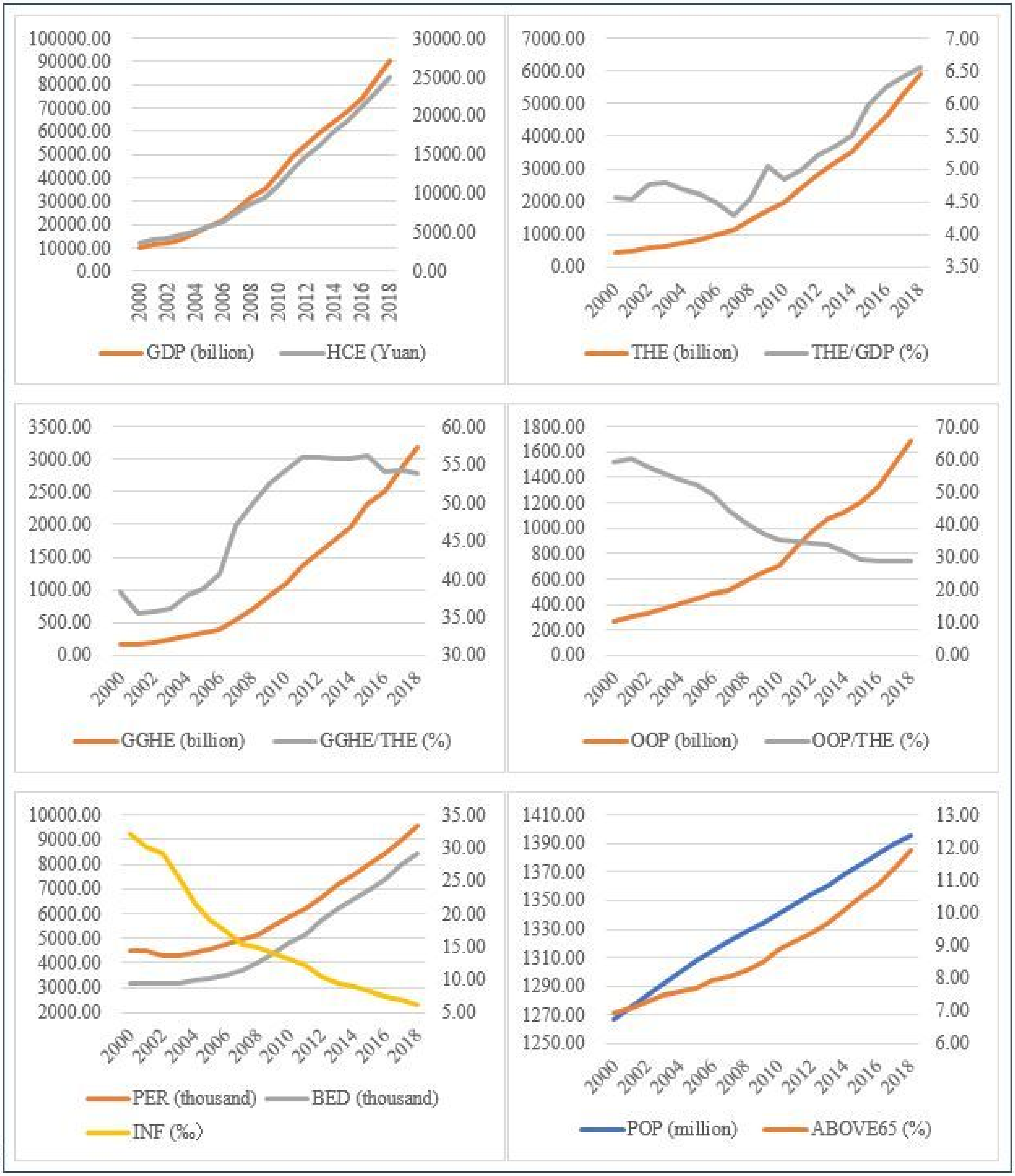


**Figure 1**

Description of total health expenditure and main driving factors

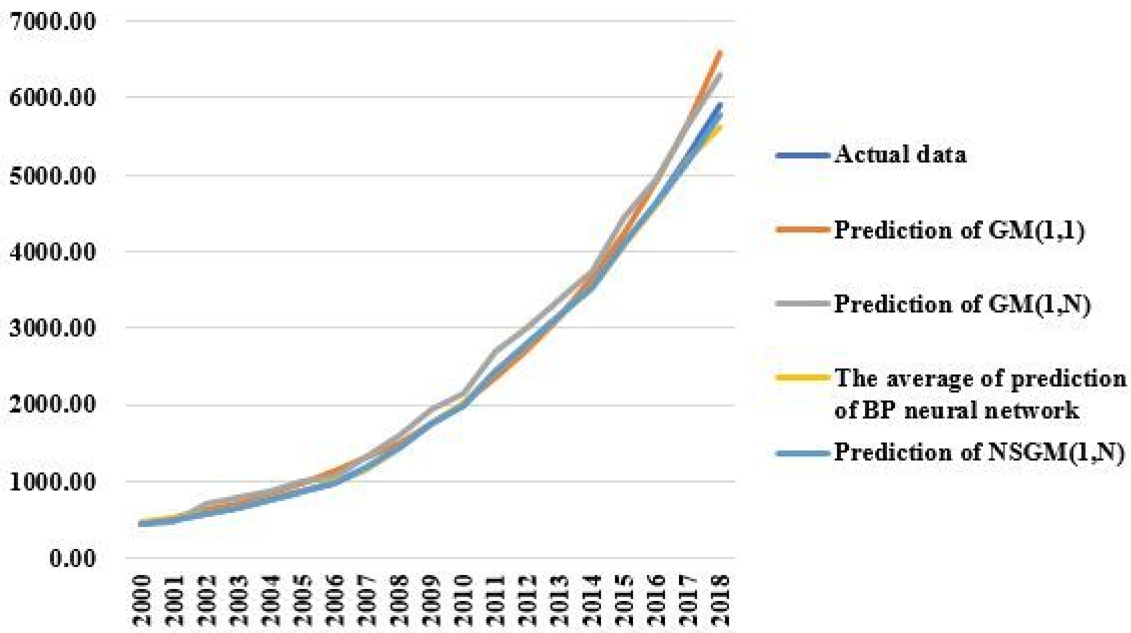


**Figure 2**

The similarity between the predictions and the actual data.