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Forecasting the Demand for Human Resources in a Hospital using the Grey Forecasting Model

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Abstract: The current study applies the grey forecasting model GM(1,1) to forecast human resource demand in a private hospital in Hebei, a province of China. With the analysis of its 2020-2024 staffing data, the model predicts a steadily increased number during 2025 to 2027. The forecast accuracy was examined by Mean Absolute Percentage Error. The study concludes with some suggestions for manpower demand management in the hospital.

Keywords: Human resource management; demand forecast; hospital; grey model; grey forecast

1. Introduction

In August 2022, China's National Health Commission issued the 14th Five-Year Plan for the Development of Health Personnel, which clearly states that the overall objective for the period is to enhance service capabilities and optimize the structure of healthcare professionals, improve personnel management systems and mechanisms, and foster a sound environment for talent development (National Health Commission, 2022). This highlights the critical role of medical, nursing, and pharmaceutical professionals in advancing the nation's healthcare system and improving the overall physical well-being of the population.

It has been observed that many previous studies have focused their main efforts on predicting the demand for health technical personnel in large population samples such as provinces and cities, or even countries. For instance, Guan *et al.* (2010), studied the numbers of medical specialists and beds between 2009 and 2020 in Chengdu mathematically using a grey forecasting model and guided by the development plans of local health administration. Liu *et al.* (2011) predicted the medical staff needs in Beijing communities using the indicators of staffing need (ISN). Scheffler and Arnold (2019) projected the shortage of doctors and nurses in Organization for Economic Co-operation and Development (OECD) countries till 2030. Huang *et al.* (2020) performed the demand forecast of health resources in Shanxi traditional Chinese medicine hospitals and annual average growth rate of medical human power. Lv *et al.* (2024) studied medical and health resources in Anhui Province from 2009 to 2020. In general, it is observed that predicting hospital-specific personnel needs, especially in the context of Hebei, is an area that requires further exploration. A very brief overview of the selected literature is shown in *Table 1*. The current study will analyze staffing data from a specific hospital in Hebei from 2020 to 2024 while constructing a grey model GM(1,1) to

Table 1. A brief overview of some studies

Year	Keywords	Study area	Methods	Literature
2010	Health Resources; Development Plan	Chengdu City	GM(1,1)	Guan *et al.* (2010)
2011	Community Health Service	Beijing communities	ISN	Liu *et al.* (2011)
2019	Health Workforce	OECD countries	ARIMA	Scheffler and Arnold (2019)
2020	Health Resources	Shanxi traditional Chinese medicine hospitals	GM(1,1)	Huang *et al.* (2020)
2024	Health Resources	Anhui Province	GM(1,1)	Lv *et al.* (2024)
2025	Hospital	A hospital in Hebei Province	GM(1,1)	The current study
NOTE: ARIMA = Autoregressive Integrated Moving Average Models, ISN = Indicators of Staffing Need				

forecast hospital personnel needs in the next few years, and compares the prediction with actual figures.

The rest of the study is organized as follow. In the second section, data collection In the third section, the model's accuracy is validated using MAPE (Mean Absolute Percentage Error), and the hospital's human resource demand over the next three years is projected for reference. In the last section, the study has been concluded.

2. Research Methodology

2.1 Data

The hospital under study is a private hospital located in Hebei, a province of the People's Republic of China. Among its popular disciplines include orthopedics and proctology. The data used in the current study was responsibly obtained from the human resources department of the hospital and was covering the years 2020 to 2024. The data included total staff numbers, age distributions, and professional title structures. The year 2025 is predicted and then compared with actual data, followed by projecting the demand of active employees in future.

2.2 Grey Model GM(1,1)

The Grey System Theory was first proposed by Professor Deng Julong in 1982. Among its major streams of research includes grey forecasting models. The grey models are characterized by low data requirements, small computational needs, and high accuracy for short- to medium-term forecasts, especially when data distribution is regular (Liu *et al.*, 2010). Given that HR demand in a hospital is influenced by factors such as medical school enrollment, residency training policies, and regional healthcare planning—factors with unclear linear relationships—this study relies solely on historical data for short-term forecasting. The current study used the classical grey forecasting model GM (1,1). WPS Office Spreadsheet tool was used for data analysis. The grey model GM model used in the current study has been adapted from Zhao *et al.* (2024).

3. Research Methodology

3.1 Basic Staffing Situation from 2020 to 2024

The staffing overview is shown in *Table 2*, with age distribution in *Table 3*. Staff transfers and deaths are excluded. From *Table 2*, staff numbers increased from 743 in 2020 to 813 in 2024, reflecting a growth rate of approximately 9.42% and an annual average growth rate of about 2.29%. The proportion of junior titles decreased, while intermediate and senior titles increased. Intermediate titles rose from 26.51% to 39.36%, and senior titles rose from 19.38% to 20.54%.

Significant data fluctuations were observed in 2022. There can be several reasons of this disturbance in data: (1) It was a post-COVID-19 period in China. It is also possible that the retirement and resignation of a small number of personnel have led to a reduction in the overall

Table 2. The distributions of total hospital staff and title

	Total Staff	Junior Titles	Intermediate Titles	Senior Titles
2020	743	402	197	144
2021	788	436	209	143
2022	779	258	353	168
2023	804	393	263	148
2024	813	326	320	167

Table 3. The distribution of staff age

	Age ≤ 23	24–33	34–43	44–53	54–63	≥64
2020	0	266	238	175	63	1
2021	2	271	268	186	61	0
2022	0	236	303	178	61	1
2023	2	225	335	179	63	0
2024	0	206	354	203	50	0

base, and (2), the policy of professional title promotion that supports front-line personnel in the fight against the COVID-19 may have resulted in a significant increase in the number of personnel with intermediate and senior professional titles. Compared to 2021, intermediate titles increased by 144 (70.85%), and senior titles increased by 25 (18.84%). However, in 2023, intermediate titles fell by 90 (-27.81%), and senior titles also decreased by 20 (-14.64%).

As shown in *Table 3*, the ≤23 and ≥64 age groups are statistically insignificant. The remaining four groups center around an average of 40.8, 299.6, 184.2, 59.6, with minimal variation.

3.2 Forecast for 2025–2027

3.2.1 GM(1,1) Model Construction. We build the original sequence $X^{(0)}$= [743, 788, 779, 804, 813] and generate the cumulative sequence $X^{(1)}$:

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i)$$

Then,

$$X^{(1)} = [X^{(1)}(1), X^{(1)}(2), X^{(1)}(3), X^{(1)}(4), X^{(1)}(5)]$$

$$X^{(1)} = [743,1531,2310,3114,3927].$$

Next, the mean adjacent sequence $Z^{(1)} = [Z^{(1)}(2), Z^{(1)}(3), Z^{(1)}(4), Z^{(1)}(5)]$ is derived:

$$Z^{(1)}(k) = \frac{1}{2}\left(X^{(1)}(k) + X^{(1)}(k-1)\right), k = 2,3,4,5$$

We then establish the grey differential equation:

$$X^{(0)}(k) + aZ^{(1)}(k) = b, k = 2,3,4,5$$

The corresponding whitened differential equation is:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b$$

Later, the least squares method is used to estimate a and b:

$$(a,b)^T = (B^T B)^{-1} B^T Y$$

Let B and Y be defined as:

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ -Z^{(1)}(4) & 1 \\ -Z^{(1)}(5) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \\ X^{(0)}(5) \end{bmatrix}$$

We find development coefficient $a = -0.013$ and grey action quantity $b = 766.692$, resulting in the time response function:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, k = 0,1,2,3,4$$

Back-transforming yields the forecasted original data sequence:

$$\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k) = (1 - e^{a}) \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}$$

For $k = 6$ (year 2025), the forecast is 821.419, aligning closely with the actual count of 808 reported in April 2025. Later, Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) or other metrics can be used to quantify the disparity between simulated and actual numbers.

3.2.2 Forecast for 2025–2027. The forecast for next three years is estimated as:

For $k = 6$ (year 2025), $\hat{X}^{(0)}(6) = 821.419$, in the vicinity of 821.

For $k = 7$ (year 2026), $\hat{X}^{(0)}(7) = 831.850$, in the vicinity of 832.

For $k = 8$ (year 2027), $\hat{X}^{(0)}(8) = 842.414$, in the vicinity of 842.

The GM(1,1) predicted a steady increase in staff over the next three years, with an annual average growth rate of approximately 1.27%. Compared to 2020, the 2027 staff count increases by 13.32%, averaging 1.8% annually. See *Figure 1* for the trend.

3.3 Forecast Error Testing

Mean Absolute Percentage Error (MAPE) is an effective measure of forecast accuracy. It uses actual and predicted values to estimate an error index that can be is interpretable in percentage terms. It is the average of the absolute percentage errors between forecasts and actuals (Duan & Nie, 2022), and is given by

$$MAPE(\%) = \frac{1}{n} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \times 100$$

where n is the number of observations, y_i is the actual value, and $\hat{y}_i$ is the forecast. The MAPE values can be interpreted using the scale shown in *Table 4*, adapted from Javed and Cudjoe (2022).

As mentioned above, the actual value of 2020-2024 were trained in grey model GM(1,1) as in-sample data, however, the MAPE value of in-sample data should also be tested to prove the model's accuracy. The authors decided to use the personnel number of 2024 to justify whether this

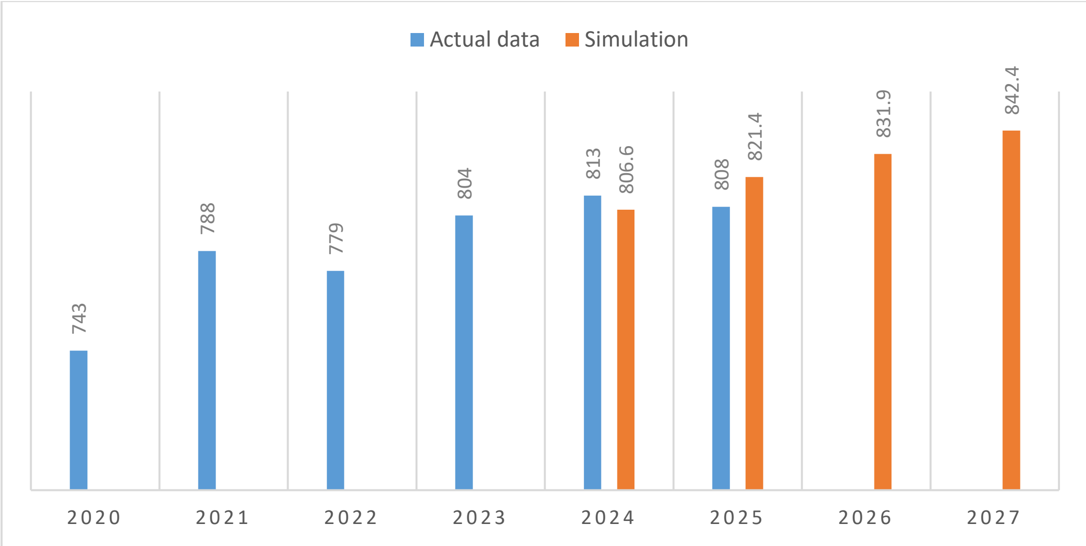

Figure 1. Actual and simulated hospital staff numbers.

Table 4. The MAPE scale

MAPE	Accuracy
<10%	Very good, high fit
10–20%	Good, acceptable error
20–30%	Moderate, large error
>30%	Poor prediction

model will be applied to predict a future human demand. The actual number of 2024 is 813 whereas the forecast is 806.579, in the vicinity of 806. And the MAPE value is 0.79%, according to MAPE scale reported in Table 4, it indicates a strong predictive accuracy. Out-sample data comes to the year of 2025. While the actual value is 808, collected at the end of April of this year, the forecast is 821.419. And, the MAPE value of GM(1,1) model in this case is 1.66%, indicating strong forecast accuracy.

4. Conclusion and recommendation

Medical staff are the backbone of hospital operations and public health progress. Their employment stability and career development directly affect healthcare quality. Currently, challenges include long training cycles (Liu & Wang, 2019) and increasing personnel loss (Chen & Chen, 2024). To align HR supply with demand, organizations should enhance the talent ecosystem on multiple levels:

4.1 Improving Promotion Systems

Establish clear, fair, and transparent promotion standards beyond tenure and academic credentials. Evaluate professional skills, work performance, research achievements, and patient satisfaction. Provide clear career paths, with distinct responsibilities and benefits per rank. Conduct regular internal training, invite industry experts for lectures, and encourage participation in domestic and international conferences and training. Collaborate with universities for continuing education programs to help staff update their knowledge and keep pace with medical advances (Cheng *et al.*, 2009).

4.2 Optimizing Compensation and Benefits

Ensure competitive pay to attract and retain talent. Link performance pay to job quality, workload, and patient satisfaction. Provide front-line staff with risk allowances. Beyond legal benefits, offer perks like commercial insurance, health checks, paid leave, holiday bonuses, discounted meals, and housing subsidies. Staff with children should be support by assisting their children with school admissions. Housing assistance for non-locals should be provided, and exceptional performance in innovation or crisis response should be rewarded with bonuses and honors.

4.3 Building a Positive Culture

Upgrade hospital facilities and equipment for a safer, more comfortable work environment. Optimize workflows and layout to reduce unnecessary burdens. Promote digitalization for faster information sharing and higher efficiency. Foster a collaborative, respectful, and patient-focused culture. Organize team-building events, birthdays, and cultural activities to strengthen cohesion and workplace relationships. Ensure smooth communication with patients to resolve disputes, uphold staff dignity, and create a safe, supportive, and worry-free environment where staff can focus on care.

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