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Prediction of population aging trend and analysis of influencing factors based on grey fractional-order and grey relational models: a case study of Jiangsu Province, China

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Abstract

Background With the rapid development of society, China is facing an increasingly serious problem of population aging. This trend poses new challenges to the labor force structure, public medical care construction and elderly care services, forcing the government to make a series of policy adjustments. Jiangsu Province, as a region with prominent aging problems in China, has a particularly significant aging phenomenon. Against the backdrop of the Chinese government's active response to the challenges of aging, this study conducts an in-depth analysis of the aging trend and its influencing factors in Jiangsu Province.

Methods Based on the statistical data of the total population and the aging population in Jiangsu Province from 2011 to 2023, this study employs the grey fractional-order prediction model (FGM(1,1)) to forecast the trend of the aging population and the aging coefficient in Jiangsu Province over the next decade. Additionally, grey relational analysis (GRA) based on panel data was conducted to thoroughly examine the relevant influencing factors of population aging in Jiangsu Province. The analysis identified key factors such as general public budget expenditure, health technicians, urbanization rate, and education level as being highly correlated with population aging.

Results The results of trend prediction indicate that the elderly population in Jiangsu Province is projected to continue increasing over the next decade, with the degree of aging becoming more pronounced. Additionally, GRA based on panel data reveals that factors such as general public budget expenditures and the number of health technicians significantly influence the aging process. This suggests that public financial investment and the quantity and quality of health technicians play crucial roles in shaping the aging trend.

Conclusions In conjunction with the analysis results from FGM(1,1) model and GRA of panel data, this study enhances the comprehensive understanding of the aging issue in Jiangsu Province. The insights derived herein offer crucial data support and a scientific foundation for both Jiangsu Province and the Chinese government to develop policies addressing population aging. Considering the anticipated future trends in aging, it is recommended that the government revise fertility policies to optimize population structure, increase investment in public

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finance and medical security, and promote the development of elderly care systems. These measures aim to mitigate the challenges posed by aging and achieve sustainable economic and social development.

Keywords Population aging, Trend prediction, Analysis of influencing factors, Grey fractional-order model, Grey relational analysis, Panel data

Introduction

On a global scale, population aging has become a social phenomenon that cannot be ignored. According to the United Nations, the number of elderly people aged 60 and over in the world is growing at an alarming rate and is expected to reach 2.1 billion by 2050, accounting for 22% of the global population. Similarly, China is facing a severe population aging. According to China's National Bureau of Statistics, the number of people aged 60 and above in China has reached 296 million in 2020, accounting for 21.1% of the total population, and the proportion is expected to exceed 30% by 2050. This demographic shift has had a profound impact on society, the economy, and the healthcare system [1]. It is of great practical significance and academic value to study population aging. First, a better understanding of aging can help formulate effective policies to deal with the attendant labor shortages, increased pension burdens, and strained health-care resources. Secondly, aging research helps to improve the quality of life of the elderly and promote healthy aging. Through scientific research, factors affecting the health and well-being of the elderly can be found, thus providing a basis for the development of targeted interventions. Finally, aging research also has important economic significance, which can reduce the social and economic burden and promote the sustainable development of society by extending the healthy life span and increasing the labor force participation rate.

Characteristics of China's population aging

Under the background of global aging, countries have their own priorities when dealing with this problem, and China's aging problem presents a unique dual characteristics. On the one hand, compared with developed countries such as Europe, the United States and Japan, China not only has a larger elderly population base, but also the aging process is significantly accelerated. Under the combined effect of long-term family planning policy and rapid urbanization process, the "4–2-1" family structure is becoming more and more common, and the traditional family pension function is gradually weakened, which puts higher requirements on the public pension service system and social security mechanism. At the same time, the huge size of the elderly population also makes the supply of social security, medical resources and elderly care services face unprecedented pressure. On the other hand, there are significant differences in the level of economic development between urban and rural areas and between regions in China, resulting in a multi-level and multi-dimensional situation of aging. In economically developed cities and eastern regions, emerging technologies and models such as smart medical care and remote care have been gradually applied to elderly care service systems. In the central and western regions and rural areas, due to the relatively insufficient infrastructure and policy implementation, the allocation of elderly care resources and the supply of medical services are still lagging behind. At the same time, the rapid development of digital transformation and big data technology has provided strong support for smart elderly care, precision medicine and "silver economy" and other fields, which not only provides a new technical path for alleviating the current pressure on elderly care, but also opens up an opportunity for the deep-level reform of the elderly care service model and social security system. Therefore, systematic research on the specific challenges and opportunities of China's aging problem can not only provide a theoretical basis for the construction of accurate and efficient coping strategies in line with national conditions, but also lay a solid practical foundation for improving the quality of life of the elderly and achieving sustainable social and economic development.

With the increasing aging of China's population, the Chinese government has taken active measures to effectively deal with the challenges brought by aging. In 2019, The State Council of China promulgated the National Medium and Long-Term Plan for Actively Responding to Population Aging (2019–2022), which defines the aging strategy and policy objectives to be promoted in the next few years [2]. The core of the plan is to build a sound service system for the elderly, including strengthening social pension insurance, promoting the development of the elderly service industry and improving the level of medical security for the elderly. In addition, the government also encourages social forces to participate in the elderly care service industry and promote the diversified development of elderly care institutions to meet the diverse needs of the elderly. The significance of actively dealing with the aging population is not only to solve the life and pension problems of the elderly, but also to stimulate the vitality and social value of the elderly. With the deepening of the aging degree, the elderly group will also become an important force for social development. By giving full play to the wisdom and experience of the elderly, we can provide more impetus and support for social development. In addition, actively responding to the aging population can also promote the upgrading of consumption and the optimization of industrial structure, and inject new impetus into economic development. Therefore, active aging is not only a matter of social security and livelihood improvement, but also an important strategy for the long-term development of the country.

Literature review of population aging research

In recent years, the accelerating trend of population aging in China and its socio-economic impact have aroused extensive academic attention. In terms of the research on the characteristics of China's aging, through the analysis of the results of the seventh national population census, Lu and Lin concluded that China's aging has obvious regional imbalance [3]. However, with the change of China's population structure in recent years, Wu and Wu found that the pattern of urban aging in China has a significant imbalance of population spatial distribution, and the regional difference of population aging in various cities is expanding [4]. In terms of the study on the social and economic impact of population aging, Yang et al. believed that the degree of population aging has a significant inhibitory effect on the economic growth of this region [5]. Chen believed that China's labor supply will fall into a huge problem, and the contradiction between population supply and demand will become more and more prominent [6]. Wang pointed out that the increasing level of aging in China has limited the improvement and upgrading of industrial structure [7]. Song and Gao found that the phenomenon of population aging has regional differences in regions with different levels of economic development [8]. In terms of ways to deal with the aging population, Hu explored ways to actively deal with the aging population under the proposition of common prosperity based on China's national conditions [9]. Li and Jin believed that to implement the major strategy of actively coping with population aging, diversified development approaches should be explored from different levels such as policy, economy, science and technology, society and environment [10]. Liu and Chen proposed that we should reshape the modernization characteristics of the elderly in China, explore the modernization path of the elderly population, and explore the management methods of the aging population community with Chinese characteristics [11]. The existing researches have made important progress in the micro mechanism and macro policy level, but the empirical analysis of aging can provide scientific data support for aging.

To predict the trend of population aging and analyze the influencing factors of population aging is not only a necessary means for the Chinese government to deal with the challenge of population aging, but also an important way to achieve the goal of active aging. Firstly, the prediction of population aging trend [12] is to better understand the development trend and scale of future aging, so as to provide a scientific basis for the government to formulate corresponding policies and measures. With the deepening of the aging degree of society, predicting the aging trend can help the government timely adjust social welfare policies such as elderly care services and medical security, effectively respond to various challenges brought by aging, protect the legitimate rights and interests of the elderly, and promote social stability and harmony. Secondly, by analyzing the influencing factors of aging [13], we can deeply understand the root causes and internal mechanisms of aging phenomenon, as well as the degree of influence of various factors on the aging trend. Through in-depth analysis of the influencing factors, the complexity and diversity of the aging problem can be more comprehensively understood, providing scientific basis for future policy formulation and practice, and promoting the society to move towards the goal of active aging.

Common population aging prediction models include census data analysis [14], population pyramid model [15], time series analysis [16], and computer simulation models (such as system dynamics models) [17]. Through the analysis of historical data and the prediction of future trends, these models can more accurately predict the growth trend of the elderly population and its possible impact on social economy. However, these models also have certain limitations. First, census data analysis and population pyramid model rely on a large number of high-quality historical data, and the accuracy and completeness of the data directly affect the reliability of the forecast results. Second, although time series analysis can reveal the time law of population change, its forecasting ability may be limited in the face of emergencies or policy changes. In addition, although computer simulation models are highly flexible and complex, their results are highly dependent on the assumptions and parameter Settings of the model, and different Settings can lead to significantly different prediction results, increasing uncertainty.

In terms of the analysis of influencing factors of aging, commonly used methods include regression analysis [18], factor analysis [19] and multilayer linear model [20]. These methods help identify key influencing factors and their interrelationships by quantitatively analyzing the degree of influence of each factor on aging. Regression analysis can reveal the direct effects of single or multiple variables on aging, while factor analysis and multilayer linear models are able to process complex multidimensional data and reveal underlying structural relationships and hierarchical differences. Although these methods are of great value in analyzing the factors affecting aging, their limitations should not be ignored. Regression analysis assumes linear relationships between variables and may fail to capture non-linear and complex interaction effects. Factor analysis depends on the quality and quantity of sample data, and the interpretation of results is subjective. Although multilayer linear models can handle complex hierarchical data, the model construction and result interpretation are complicated and susceptible to sample bias and model setting.

Grey system theory is a system analysis method proposed by Deng in 1982. It is mainly used to deal with incomplete, inadequate and uncertain information, especially for problems with small amount of data, poor quality or large uncertainty [21, 22]. Its core contents include grey prediction model and grey relational analysis. By generating, sorting and processing the original data, the grey fractional-order model [23] constructs data series and makes trend prediction, which is suitable for the situation where the data volume is small and the trend of change is obvious. Grey relational analysis [24] is used to calculate and analyze the relational degree among various factors in the system, and reveal their mutual relations by quantifying the similarities and differences among different factors. This model system has been widely applied in economic, social and ecological system fields such as industry, agriculture, energy and transportation [25–29]. In the field of population aging research, FGM(1,1) has been widely used to analyze and predict the changing trend of the number of elderly people, changes in age structure and regional distribution [30–32]. The research shows that the FGM(1,1) has good prediction accuracy and reliability, especially it can effectively deal with the situation of incomplete or insufficient data, which is helpful to the government and relevant institutions in the elderly care service and social resource allocation in advance planning. GRA is used to evaluate the key factors affecting population aging, such as economic growth, medical and health level, social security system, etc. [33–35]. By calculating the grey relational degree between each factor and population aging, we can identify the variables that have the greatest impact on the aging process, and then provide scientific basis for policy making.

Contribution and innovation

This paper takes Jiangsu Province, a prominent area of population aging in China, as an example. Based on the number of the elderly population in Jiangsu Province from 2011 to 2023, this paper uses the grey fractional-order prediction model (FGM(1,1)) to forecast the trend of the elderly population in Jiangsu Province in the next ten years. At the same time, the grey relation analysis (GRA) based on panel data is used to analyze the influencing factors of population aging in Jiangsu Province. Finally, combining the analysis results of FGM(1,1) and GRA based on panel data, the paper puts forward some measures and suggestions to actively cope with the aging problem in Jiangsu Province and China.

The contributions and innovations of this paper mainly include the following two aspects:

(1) Based on the theory of grey system, FGM(1,1) accurately depicts the dynamic changes of data by means of fraction-order accumulation generation, breaks the shackles of traditional integer order models, and captures complex nonlinear trends with sensitivity. Compared with time series analysis, it abandons the strict data stationarity requirement, and can still model effectively under the condition of less data and non-stationarity. Compared with the regression model, FGM(1,1) does not rely on massive historical data to build complex variable relationships, has loose requirements on sample integrity, and has better prediction performance under the scenario of data scarcity or difficult explicit expression of data rules. In terms of population aging trend prediction, FGM(1,1) can more accurately capture the complex nonlinear characteristics and potential laws of population aging data, effectively improve the prediction accuracy, and provide more reliable data support for the formulation of scientific and reasonable population policies.

(2) GRA based on panel data can effectively integrate the individual and time dimension information contained in panel data, overcome the limitation of the traditional model's single dimension analysis, and comprehensively and dynamically reflect the internal relationship between data. In the analysis of influencing factors, it does not need a large number of sample data, and has relatively loose requirements on data distribution, which is suitable for the case of limited data or irregular distribution. At the same time, GRA based on panel data can clearly identify the primary and secondary correlation between the factors, and intuitively show the relative importance of the influencing factors. In the analysis of influencing factors of aging, GRA based on panel data is used to comprehensively consider the dynamic correlation of multiple influencing fac-

tors of aging in different regions and different time dimensions, and clearly identify the primary and secondary relationship of each factor's influence on the aging process, laying a foundation for in-depth understanding of the aging phenomenon and formulating coping strategies.

Organization and framework

The remainder of this paper is organized as follows. Sect. "Methods" introduces the definition and solution of FGM(1,1) model, and describes the detailed analysis method of GRA based on panel data. Sect. "Results" introduces the data sources of aging population statistics of Jiangsu Province, and gives the prediction results of population aging trend and relational degree analysis of influencing factors of population aging in Jiangsu Province. In Sect. "Discussion", the characteristics analysis of population aging trend in Jiangsu Province, and some suggestions on actively respond to the population aging are put forward. Finally, some conclusions are drawn in Sect. "Conclusions and Future Work".

Methods

In this section, the grey fractional-order model (FGM(1,1)) and grey relational analysis (GRA) based on panel data are introduced.

Grey fractional-order prediction model (FGM(1,1))

FGM(1,1) is a development and extension of grey system theory, which is based on the introduction of fractional calculus. The accuracy and applicability of traditional grey prediction models (such as GM(1,1) model) are further improved [36, 37]. The basic idea is to smooth the original data by constructing fractional order cumulative generated sequences, and then use grey differential equations for modeling and prediction. Compared with the integer order grey model, FGM(1,1) can capture the dynamic characteristics of the system more flexibly, especially in the processing of complex and nonlinear time series data. FGM(1,1) not only inherits the powerful ability of grey system theory in dealing with small samples and uncertain information, but also realizes a more precise description of the memory characteristics of the system by adjusting the fractional order parameters, thus improving the accuracy and stability of the prediction. As an important part of the grey prediction model system, FGM(1,1) extends the application scope of the grey system theory and shows superior performance and broad prospects in practical applications [38, 39].

Basic form of grey fractional-order model

Step 1: Set the original non-negative sequence $X^{(0)}=\left(x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\right)$, $x^{(r)}(k)=\sum_{i=1}^{k}x^{(r-1)}(i)$ is the r-order accumulation operator, then $x^{(r)}(k)=\sum_{i=1}^{k}C_{k-i+r-1}^{k-r}x^{(0)}(i)$, where $C_{k-i+r-1}^{k-i}=\frac{(k-i+r-1)(k-i+r-2)\cdots(r+1)r}{(k-i)!}$, $C_{r-1}^{0}=1$, $C_{k}^{k+1}=0$. The r-order accumulation sequence of $X^{(0)}$ can be obtained as

$$X^{(r)}=\left(x^{(r)}(1),x^{(r)}(2),\cdots,x^{(r)}(n)\right) \tag{1}$$

Then the adjacent mean generating sequence $X^{(r)}$ is

$$Z^{(r)}=\left(z^{(r)}(2),z^{(r)}(3),\cdots,z^{(r)}(n)\right) \tag{2}$$

where $z^{(r)}(k)=\frac{1}{2}\left(x^{(r)}(k)+x^{(r)}(k-1)\right)$, $k=2,3,\cdots,n$.

Step 2: The basic form of the FGM(1,1) model is

$$x^{(r-1)}(k)+az^{(r)}(k)=b \tag{3}$$

In particular, when $r=1$, there is $X^{(r)}=X^{(1)}$, and $X^{(1)}$ is the one-time accumulation generation operator. Then Eq. (3) becomes $x^{(0)}(k)+az^{(1)}(k)=b$, which is the traditional GM(1,1) model.

The whitening equation of FGM(1,1) model is

$$\frac{dx^{(r)}(t)}{dt}+ax^{(r)}(t)=b \tag{4}$$

where, a is the development coefficient, b is the grey action.

Step 3: The parameter vector $\hat{a}=[a,b]^{T}$ can be obtained by using the least squares estimation $\hat{a}=\left(B^{T}B\right)^{-1}B^{T}Y$, where Y and B are as follows:

$$Y=\begin{bmatrix} x^{(r)}(2)-x^{(r)}(1) \\ x^{(r)}(3)-x^{(r)}(2) \\ \vdots \\ x^{(r)}(n)-x^{(r)}(n-1) \end{bmatrix},\ B=\begin{bmatrix} -\frac{1}{2}\left(x^{(r)}(1)+x^{(r)}(2)\right) & 1 \\ -\frac{1}{2}\left(x^{(r)}(2)+x^{(r)}(3)\right) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left(x^{(r)}(n-1)+x^{(r)}(n)\right) & 1 \end{bmatrix} \tag{5}$$

Step 4: Under the initial condition $x^{(0)}(1)=x^{(r)}(1)$, the time response function of the whitening equation $\frac{dx^{(r)}(t)}{dt}+ax^{(r)}(t)=b$ is

$$x^{(r)}(t)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(t-1)}+\frac{b}{a},\ t=2,3,\cdots,n \tag{6}$$

Then the time response sequence of grey differential equation $x^{(0)}(k)+az^{(r)}(k)=b$ of FGM(1,1) model is

$$\hat{x}^{(r)}(k)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)}+\frac{b}{a},k=2,3,\cdots,n \tag{7}$$

where, $\hat{x}^{(r)}(k)$ is the value at time k, and the predicted value is obtained by reducing $\hat{x}^{(r)}(k)$ as follows

$$\hat{x}^{(0)}(k) = \alpha^{(r)}\hat{x}^{(r)}(k) = \hat{x}^{(r)(1-r)}(k) - \hat{x}^{(r)(1-r)}(k-1),\ k = 2, 3, \cdots, n \tag{8}$$

PSO optimization algorithm for model parameters

For FGM(1,1), the most important thing is to determine the optimal fractional order r. Different accumulation order r will produce different results on the final prediction accuracy. Because the traditional method needs a lot of operations to determine the optimal order, in order to improve the efficiency of the operation, the particle swarm optimization algorithm in the modern optimization algorithm is used to solve the problem of selecting the optimal order. Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart in 1995 [40]. The algorithm was inspired by the predation behavior of bird and fish clusters as a simulation of a simple social model, primarily inspired by animal behavior.

The basic process of the PSO optimization algorithm is described as follows: assume that there are m particles in the D-dimensional target search space, and the potential solutions in the target space are determined by the position of each particle. The D-dimensional position coordinate of the i-th particle is $X_i = \left(x_i^1, x_i^2, \cdots, x_i^D\right)$ and the velocity vector is $V_i = \left(v_i^1, v_i^2, \cdots, v_i^D\right)$. Each iteration, the particle velocity is updated according to the individual extreme value p_{best} and the global extreme value g_{best}, and the formula for calculating the velocity change is

$$V_{i+1} = wv_i^d + c_1r_1\left(p_i^d - x_i^d\right) + c_2r_2\left(p_g^d - x_i^d\right) \tag{9}$$

where, V_{i+1} is the velocity of the particle after the $i+1$ iteration update, w is the inertial vector,c_1 and c_2 are acceleration constants, and the value range of r_1 and r_2 is $[0, 1]$, usually $c_1 = c_2 = 2$, particle velocity v_i will be limited by the maximum velocity $v_{\max}$.

In each iteration, the particle position is updated according to the velocity vector and position vector, and the formula for determining the particle position is

$$x_{i+1} = x_i + v_i \tag{10}$$

where x_{i+1} is the particle position after the update of the $i+1$ iteration.

The general algorithm terminates at the optimal position found by the particle swarm, that is, the minimum adaptation threshold has been found to satisfy the target condition, or the algorithm has reached the maximum number of iterations. According to the algorithm principle, the minimum adaptation threshold of Mean Absolute Percentage Error (MAPE) of the algorithm search to the model is set as the termination condition, where

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)}\right| \times 100\% \tag{11}$$

Grey relational analysis (GRA) based on panel data

The general abstract system contains many factors, the result of which determines the development of the system. In the system analysis, it is more to determine which factors are the main factors and which are the secondary factors. GRA is a theory to determine the comparative advantages of the main factors from multiple factors of the system. It quantitatively describes the relationship between the internal structures of the system, and is a dynamic quantitative comparative analysis method [41]. GRA is one of the key techniques in grey system theory, which is used to quantitatively measure and analyze the degree of relation between various factors in the system. By calculating the relational coefficient, GRA can reveal the relationship between variables and their dynamic changes in the system, which is especially suitable for complex systems dealing with small samples and uncertain data. Compared with the traditional correlation analysis methods, GRA does not depend on the statistical distribution and sample size of the data, and has strong robustness and flexibility. Its main advantages include simple calculation, intuitive results, ability to handle incomplete information and wide application range. These characteristics make GRA widely used in the study of multivariate relations and decision support in the fields of economy, society and engineering, and become an important tool for the study and application of grey system theory, which greatly promotes the understanding and analysis of complex systems.

Basic mechanism of grey relational analysis

Step 1: Determine the reference sequence and comparison sequence, and carry out dimensionless data processing.

There are reference sequence $X_0 = \{x_0(1), x_0(2), \cdots, x_0(n)\}$ and m comparison sequences $X_i = \{x_i(1), x_i(2), \cdots, x_i(n)\}$, where $i = 1, 2, \cdots, m$. Initialize the reference sequence X_0 and the comparison sequences X_i to eliminate dimensional effects:

$$x_0'(t) = \frac{x_0(t)}{x_0(1)},\ x_i'(t) = \frac{x_i(t)}{x_i(1)},\ t = 1, 2, \cdots, n \tag{12}$$

Then the initialized reference sequence X_0' and comparison sequences X_i' are obtained.

Step 2: Calculate the absolute difference and its extreme value.

Calculate the absolute difference $\Delta_i(t) = \left|x_0'(t) - x_i'(t)\right|$ between the reference sequence X_0' and each comparison sequences X_i' at each time point t, and then calculate the minimum and maximum of all the absolute differences: $\Delta_{\min} = \min\limits_{i,t} \Delta_i(t)$, $\Delta_{\max} = \max\limits_{i,t} \Delta_i(t)$.

Step 3: Calculate the grey relational coefficient.

Based on the absolute difference $\Delta_i(t)$, minimum $\Delta_{\min}$, and maximum $\Delta_{\max}$, calculate the grey relational coefficient for each comparison sequencesc X_i' at each time point t:

$$\xi_i(t) = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_i(t) + \rho\Delta_{\max}} \tag{13}$$

where ρ is the resolution coefficient, usually $\rho = 0.5$.

Step 4: Calculate the grey relational degree.

Calculate the grey relational degree $\gamma_i = \frac{1}{n}\sum\limits_{t=1}^{n} \xi_i(t)$ for each comparison sequences X_i', which is the average relational coefficient over the entire time range.

Step 5: Sort and analyze.

According to the calculated grey relational degree γ_i, all comparison sequences X_i are sorted. The greater the correlation degree γ_i, the higher the relational degree between the comparison sequence X_i and the reference sequence X_0.

Grey relational degree based on panel data

GRA based on panel data is a new method combining grey system theory and panel data analysis technology [42, 43]. This method can not only process multi-dimensional time sequences data, but also make full use of the double information of cross section and time sequences in panel data to improve the accuracy and robustness of analysis results. Through dimensionless processing of multidimensional data, it calculates the grey relational coefficient between each variable, and evaluates the relational degree between variables. Compared with the traditional GRA, the method based on panel data has significant advantages. It is capable of processing complex data structures with both time sequences and cross-sectional dimensions, and is suitable for dynamic and cross-regional research. By making full use of the rich information contained in the panel data, the method improves the accuracy and reliability of the analysis. In addition, combined with the characteristics of panel data, the method can better resist the influence of data fluctuations and outliers on the analysis results.

Definition 1 [44]**:** Let $x_n(m,t)$ be the observed value of the m-th object $(m = 1, 2, \cdots, M)$ of the n-th indicator $(n = 1, 2, \cdots, N)$ at the time $t (t = 1, 2, \cdots, T)$, then the panel data of the n-th indicator is $X_n = \begin{bmatrix} x_n(1,1) & x_n(1,2) & \cdots & x_n(1,T) \\ x_n(2,1) & x_n(2,2) & \cdots & x_n(2,T) \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1) & x_n(M,2) & \cdots & x_n(M,T) \end{bmatrix}$. Let $x_m(n,t)$ be the observed value of the m-th object $(m = 1, 2, \cdots, M)$ of the n-th indicator $(n = 1, 2, \cdots, N)$ at the time t $(t = 1, 2, \cdots, T)$, then the panel data of the m-th object is $X_m = \begin{bmatrix} x_m(1,1) & x_m(1,2) & \cdots & x_m(1,T) \\ x_m(2,1) & x_m(2,2) & \cdots & x_m(2,T) \\ \vdots & \vdots & \ddots & \vdots \\ x_m(N,1) & x_m(N,2) & \cdots & x_m(N,T) \end{bmatrix}$. Let $x_t(m,n)$ be the observed value of the m-th object $(m = 1, 2, \cdots, M)$ about the n-th indicator $(n = 1, 2, \cdots, N)$ at the time t $(t = 1, 2, \cdots, T)$, then the panel data at time t is $X_t = \begin{bmatrix} x_t(1,1) & x_t(1,2) & \cdots & x_t(1,N) \\ x_t(2,1) & x_t(2,2) & \cdots & x_t(2,N) \\ \vdots & \vdots & \ddots & \vdots \\ x_t(M,1) & x_t(M,2) & \cdots & x_t(M,N) \end{bmatrix}$.

Definition 2 [44]**:** Let the panel data of the n-th indicator be X_n, $n = 1, 2, \cdots, N$, let D_1 be the sequence operator, and.

$$X_nD_1 = \begin{bmatrix} x_n(1,1)d_1 & x_n(1,2)d_1 & \cdots & x_n(1,T)d_1 \\ x_n(2,1)d_1 & x_n(2,2)d_1 & \cdots & x_n(2,T)d_1 \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1)d_1 & x_n(M,2)d_1 & \cdots & x_n(M,T)d_1 \end{bmatrix} \tag{14}$$

where $x_n(m,t)d_1 = MTx_n(m,t) / \sum\limits_{m=1}^{M}\sum\limits_{t=1}^{T} x_n(m,t)$, $m = 1, 2, \cdots, M$, and $t = 1, 2, \cdots, T$, then D_1 is called the averaging operator of panel data.

Let D_2 be a sequence operator, and

$$X_nD_2 = \begin{bmatrix} x_n(1,1)d_2 & x_n(1,2)d_2 & \cdots & x_n(1,T)d_2 \\ x_n(2,1)d_2 & x_n(2,2)d_2 & \cdots & x_n(2,T)d_2 \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1)d_2 & x_n(M,2)d_2 & \cdots & x_n(M,T)d_2 \end{bmatrix} \tag{15}$$

where $x_n(m,t)d_2 = x_n(m,t) - x_n(1,1)$, $m = 1, 2, \cdots, M$, and $t = 1, 2, \cdots, T$, then D_2 is called the initial point zeroing operator of panel data.

Let D_3 be a sequence operator, and

$$X_nD_3 = \begin{bmatrix} x_n(1,1)d_3 & x_n(1,2)d_3 & \cdots & x_n(1,T)d_3 \\ x_n(2,1)d_3 & x_n(2,2)d_3 & \cdots & x_n(2,T)d_3 \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1)d_3 & x_n(M,2)d_3 & \cdots & x_n(M,T)d_3 \end{bmatrix} \tag{16}$$

where $x_n(m,t)d_3 = \frac{x_n(m,t)}{x_n(1,1)}$, $x_n(1,1) \neq 0$, $m = 1, 2, \cdots, M$, and $t = 1, 2, \cdots, T$, then D_3 is called the initial value operator of panel data.

Let D_4 be a sequence operator, and

$$X_n D_4 = \begin{bmatrix} x_n(1,1)d_4 & x_n(1,2)d_4 & \cdots & x_n(1,T)d_4 \\ x_n(2,1)d_4 & x_n(2,2)d_4 & \cdots & x_n(2,T)d_4 \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1)d_4 & x_n(M,2)d_4 & \cdots & x_n(M,T)d_4 \end{bmatrix} \quad (17)$$

where $x_n(m,t)d_4 = \frac{x_n(m,t) - \min\limits_m \min\limits_t x_n(m,t)}{\max\limits_m \max\limits_t x_n(m,t) - \min\limits_m \min\limits_t x_n(m,t)}$, $\max\limits_m \max\limits_t x_n(m,t) - \min\limits_m \min\limits_t x_n(m,t) \neq 0$, $m = 1, 2, \cdots, M$, and $t = 1, 2, \cdots, T$, then D_4 is called the intervalization operator of panel data.

Definition 3: Let $X_0, X_1, X_2, \cdots, X_N$ be the panel data sequence, where X_0 is the reference sequence and $X_n (n = 1, 2, \cdots, N)$ are the comparison sequences. After initialization, the comparison sequences $X_n = \begin{bmatrix} x_n(1,1) & x_n(1,2) & \cdots & x_n(1,T) \\ x_n(2,1) & x_n(2,2) & \cdots & x_n(2,T) \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1) & x_n(M,2) & \cdots & x_n(M,T) \end{bmatrix}$ can be obtained as follows:

$$X_n D = \begin{bmatrix} x_n(1,1)d & x_n(1,2)d & \cdots & x_n(1,T)d \\ x_n(2,1)d & x_n(2,2)d & \cdots & x_n(2,T)d \\ \vdots & \vdots & \ddots & \vdots \\ x_n(M,1)d & x_n(M,2)d & \cdots & x_n(M,T)d \end{bmatrix} \quad (18)$$

Then

$$\gamma_{0n}(m,t) = \frac{s + 0.5S}{\left| x_0(m,t)d - x_n(m,t)d \right| + 0.5S} \quad (19)$$

is called the distance correlation coefficient between panel data X_0 and X_n, where $s = \min\limits_n \min\limits_m \min\limits_t \left| x_0(m,t)d - x_n(m,t)d \right|$, $S = \max\limits_n \max\limits_m \max\limits_t \left| x_0(m,t)d - x_n(m,t)d \right|$ (20).

Definition 4: Let $X_0, X_1, X_2, \cdots, X_N$ be the panel data sequences, where X_0 is the reference sequence and $X_n (n = 1, 2, \cdots, N)$ are the comparison sequences, then

$$\Upsilon_{0n} = \frac{1}{M \times T} \sum_{m=1}^{M} \sum_{t=1}^{T} \gamma_{0n}(x_0(m,t), x_n(m,t)) \quad (21)$$

is called the grey relational degree of panel data.

Results

Current situation of population structure in Jiangsu Province

As a typical sample in the process of population aging in China, the case study of Jiangsu Province has significant theoretical value and policy implications. By the end of 2023, the number of permanent elderly residents aged 60 and above in Jiangsu Province reached 20.89 million, accounting for 24.5% of the permanent population. The proportion of registered elderly people is 26%, far exceeding the national average (21.1%). The aging population ranks third in China, behind only Shanghai and Beijing. The formation of this phenomenon is not only due to the general law of declining fertility and increasing life expectancy, but also influenced by the characteristics of regional population migration. In southern Jiangsu, the aging rate is partially diluted by the inflow of migrant young and middle-aged labor, while in central and northern Jiangsu, the aging problem is aggravated by the outflow of local young and middle-aged people. Among them, the proportion of registered elderly over 60 in Nantong City exceeds 30%, becoming one of the prefecture-level cities with the highest aging rate in the country.

The structural characteristics of population aging in Jiangsu Province are the coexistence of "aging" and "vitality at a younger age". On the one hand, the elderly population aged 80 and above exceeded 3,078,900, accounting for 15.07% of the registered elderly population, and the number of centenarians increased to 8,683, showing a significant trend of longevity. On the other hand, the young active elderly aged 60–69 accounted for 50.41% of the total elderly population, and their re-employment rate reached 30.41%, reflecting the dual attributes of the development potential of human resources and the demand for social and economic participation of the elderly. It is worth noting that the elderly dependency ratio has climbed to 27.14%, and the proportion of rural left-behind elderly and disabled and mentally retarded groups has increased (especially in northern Jiangsu), making the systematic pressure of medical resource allocation and long-term care service supply continue to highlight.

Prediction of population aging in Jiangsu Province

According to the Statistical Yearbook of Jiangsu Province [45] and the Jiangsu Province Aging Cause Development Report [46] of each year, the statistical data of the registered population, the elderly population over 65 years old and the ratio of aging coefficient in Jiangsu Province from 2011 to 2023 were sorted out, as shown in Table 1.

With the statistical data of the registered population of Jiangsu Province from 2011 to 2021 as the fitting sample for modeling, and the statistical data from 2022–2023 as the forecasting sample, the FGM(1,1) model for the total population prediction is established as

$$\hat{x}^{(r)}(k+1) = \left[x^{(0)}(1) - \frac{1549.1317}{0.1872} \right] e^{-0.1872k} + \frac{1549.1317}{0.1872} \quad (22)$$

where the optimal order $r = 0.0119$ is determined by PSO optimization algorithm. The FGM(1,1) model

Table 1 Total registered population, elderly population over 65 years old and aging coefficient of Jiangsu Province from 2011 to 2023

Year	2011	2012	2013	2014	2015	2016	2017
Total population (10,000)	7514.25	7553.48	7616.84	7684.69	7717.59	7775.66	7794.19
Population over 65 (10,000)	941.28	970.37	1017.94	1072.47	1115.08	1167.55	1199.91
Aging coefficient	12.54%	12.87%	13.38%	13.97%	14.45%	15.01%	15.38%
Year	2018	2019	2020	2021	2022	2023	
Total population (10,000)	7813.86	7858.27	7876.75	7881.70	7872.00	7852.36	
Population over 65 (10,000)	1256.45	1330.29	1387.92	1443.95	1522.00	1540.55	
Aging coefficient	16.03%	16.91%	17.62%	18.32%	19.33%	19.60%	

Table 2 The fitting and predicted values of the total registered population in Jiangsu Province from 2011 to 2023 under three comparison models

Year	Total population (10,000)	FGM(1,1)		DES		Logistic	
		Predicted value (10,000)	APE (%)	Predicted value (10,000)	APE (%)	Predicted value (10,000)	APE (%)
2011	7514.25	7514.25	0.00	7514.25	0.00	7501.81	0.17
2012	7553.48	7554.75	0.02	7553.48	0.00	7568.24	0.20
2013	7616.84	7616.71	0.00	7607.19	0.13	7626.49	0.13
2014	7684.69	7674.63	0.13	7672.86	0.15	7677.46	0.09
2015	7717.59	7724.52	0.09	7723.12	0.07	7721.98	0.06
2016	7775.66	7766.18	0.12	7776.08	0.01	7760.79	0.19
2017	7794.19	7800.35	0.08	7808.23	0.18	7794.58	0.01
2018	7813.86	7828.04	0.18	7827.84	0.18	7823.97	0.13
2019	7858.27	7850.22	0.10	7857.29	0.01	7849.49	0.11
2020	7876.75	7867.77	0.11	7880.52	0.05	7871.64	0.06
2021	7881.70	7881.48	0.00	7891.42	0.12	7890.84	0.12
MAPE (%)			0.076		0.082		0.114
2022	7872.00	7892.01	0.25	7908.15	0.46	7907.48	0.45
2023	7852.36	7899.92	0.61	7924.89	0.92	7921.89	0.89
MAPE (%)			0.430		0.691		0.668

established above was compared with the double exponential smoothing method (DES) and Logistic regression model (Logistic), and error analysis was carried out at the same time. The fitting and predicted values of each model and the error analysis results were shown in Table 2.

The FGM(1,1) model for predicting the number of elderly people over 65 years old is established as

$$\hat{x}^{(r)}(k+1) = \left[x^{(0)}(1) + \frac{895.2791}{0.0413}\right]e^{0.0413k} - \frac{895.2791}{0.0413} \tag{23}$$

where the optimal order $r = 0.9605$ is determined by PSO optimization algorithm. It was compared with DES and Logistic, and error analysis was carried out at the same time. The fitting and predicted values of each model and the error analysis results were shown in Table 3.

As can be seen from Table 2 and Table 3, compared with DES and Logistic, FGM(1,1) model has the smallest prediction error in the fitting area and prediction area on the whole. Therefore, from a comprehensive point of view, FGM(1,1) model has the best prediction effect on population aging trend. FGM(1,1) model was used to forecast the total population and the elderly population of Jiangsu Province in the next 10 years, and the corresponding predicted aging coefficient was obtained, as shown in Table 4.

The prediction results show that in the future period, with the continuous advancement of time, the aging of population in Jiangsu Province is showing a significant trend of increasing year by year. By the end of 2023, the aging coefficient of Jiangsu Province has reached 19.60%, which directly reflects that the proportion of the elderly

Table 3 The fitting and predicted values of the elderly population over 65 years old in Jiangsu Province from 2011 to 2023 under three comparison models

Year	Population over 65 (10,000)	FGM(1,1)		DES		Logistic	
		Predicted value (10,000)	APE (%)	Predicted value (10,000)	APE (%)	Predicted value (10,000)	APE (%)
2011	941.28	941.28	0.00	941.28	0.00	933.36	0.84
2012	970.37	961.27	0.94	970.37	0.00	975.76	0.56
2013	1017.94	1015.49	0.24	1005.00	1.27	1019.90	0.19
2014	1072.47	1066.63	0.54	1047.65	2.31	1065.82	0.62
2015	1115.08	1116.93	0.17	1093.85	1.90	1113.58	0.13
2016	1167.55	1167.44	0.01	1145.19	1.92	1163.23	0.37
2017	1199.91	1218.71	1.57	1194.18	0.48	1214.82	1.24
2018	1256.45	1271.10	1.17	1246.30	0.81	1268.41	0.95
2019	1330.29	1324.86	0.41	1306.46	1.79	1324.04	0.47
2020	1387.92	1380.19	0.56	1369.44	1.33	1381.76	0.44
2021	1443.95	1437.23	0.47	1433.10	0.75	1441.63	0.16
MAPE (%)			0.551		1.142		0.544
2022	1522.00	1496.13	1.70	1494.44	1.81	1503.68	1.20
2023	1540.55	1557.02	1.07	1555.77	0.99	1567.97	1.78
MAPE (%)			1.384		1.400		1.492

in the total population in the province has been close to one-fifth. What is more serious is that according to the current population development dynamics and trends, by the end of 2033, the number of elderly people aged 65 and above in Jiangsu Province is expected to rise sharply to 23,573,300, and the aging coefficient will rise sharply to 30.08%, which means that there are three elderly people in every ten people in the province, and the imbalance of population age structure is becoming more prominent.

Relational degree analysis of influencing factors of population aging in Jiangsu Province

Source of samples and data

When conducting correlation analysis on the influence factors of population aging in Jiangsu Province, Nantong, Nanjing, Suzhou and Xuzhou, four cities with aging characteristics, were selected as samples. As a well-known longevity town, Nantong has a high degree of aging in the whole province. It has a significant aging population, a high empty nest rate, and a large outflow of young labor force, which weakens the function of family pension and urgently needs community pension. Nanjing, the provincial capital, presents a situation of "rich and old", with the elderly population having a high degree of education and considerable potential for cultural consumption. Although it has high-quality medical resources, the supply and demand of medical services in the central city are unbalanced. Suzhou has developed economy, good economic security for the elderly and active consumer market. The results of urban and rural elderly care coordination are remarkable, and the forms of elderly care services are diverse. Due to the industrial transformation in Xuzhou, some workers have retired early, and the problem of aging in rural areas is significant and labor is scarce. Its pension infrastructure is backward, and the mode of mutual aid pension is gradually emerging.

Table 4 Predicted values of total population, aging population and aging coefficient of Jiangsu Province in the next 10 years

Year	2024	2025	2026	2027	2028
Total population (10,000)	7865.16	7864.38	7862.51	7859.81	7856.51
Population over 65 (10,000)	1629.03	1697.70	1769.12	1843.43	1920.76
Aging coefficient	20.71%	21.59%	22.50%	23.45%	24.45%
Year	2029	2030	2031	2032	2033
Total population (10,000)	7852.77	7848.72	7844.46	7840.07	7835.61
Population over 65 (10,000)	2001.23	2084.97	2172.14	2262.88	2357.33
Aging coefficient	25.48%	26.56%	27.69%	28.86%	30.08%

Geographical representation Nantong is located in the coastal area of central Jiangsu, Nanjing is located in the central part of southern Jiangsu, Suzhou represents the core area of the developed Yangtze River Delta in southern Jiangsu, and Xuzhou is located in northern Jiangsu. These four cities cover different regions of Jiangsu, including southern Jiangsu, Central Jiangsu and Northern Jiangsu, with significant differences in economic development gradients, which can present population aging models under different economic levels and industrial structures.

Representative economic structure Nanjing, as the provincial capital, is the center of politics, culture, science and education, and the tertiary industry is developed; Suzhou is a model of export-oriented economy, with deep integration of manufacturing and modern service industries. Based on traditional industries such as textile and construction, new industries have gradually emerged in Nantong in recent years. As a traditional industrial base and a large agricultural city, Xuzhou is promoting industrial transformation. Diverse economic structures bring different employment opportunities and labor flow patterns, and have different impacts on the process of population aging. Selecting them is conducive to a comprehensive analysis of the internal relationship between economy and aging.

Representative urbanization process The urbanization rate of Nanjing and Suzhou is quite high, and the problem of urban elderly population focuses on urban planning and fine distribution of public services. Nantong has a significant urban–rural dual structure and is in the process of rapid urbanization. In the process of urbanization in Xuzhou, there are not only new problems derived from urban expansion, but also old age dilemma caused by rural decay. A comprehensive study of these four cities can provide insight into strategies for coping with aging at different stages of urbanization.

In summary, Nantong, Nanjing, Suzhou and Xuzhou, with their unique characteristics of population aging and their regional, economic, urbanization and other aspects of representation, can provide comprehensive, in-depth and valuable samples for the correlation analysis of influencing factors of population aging in Jiangsu province, effectively making up for the deficiencies of the study on macro data of the whole province. Accurately excavate deep-seated influencing factors and coping paths.

And year 2016 is a key year for Jiangsu Province and even the whole country's population policy transition. This year, Jiangsu Province formulated the "13th Five-Year Plan for Population Development in Jiangsu Province", which is not only a scientific forecast of the population development trend in the next five years, but also a strategic deployment for the coordinated development of population and economy, society, resources and environment. The plan clearly puts forward a series of policy guidance aimed at optimizing the population structure, improving the quality of the population, and promoting the reasonable distribution of the population, laying a policy foundation for coping with the upcoming challenges of aging. Secondly, year 2016 is also the year of the official implementation of the national two-child policy. The major policy adjustment aims to encourage eligible couples to have a second child by relaxing birth restrictions, in hopes of adjusting the population structure, increasing the supply of young workers and easing the pressure of an aging population. As an economically developed and densely populated area, Jiangsu Province's response and implementation of the universal two-child policy has exemplary significance for the whole country. At the same time, the improvement of medical and health conditions has extended the average life expectancy, resulting in a relative increase in the proportion of elderly people, further aggravating the phenomenon of aging.

Therefore, statistical data [45] of four cities (Nanjing, Suzhou, Nantong and Xuzhou) from 2016 to 2023 are selected as panel data, and the number of elderly population (X_0) is taken as the reference sequence. At the same time, the gross domestic product (X_1), the per capita disposable income of urban households (X_2), the total value of exports (X_3), the general public budget expenditure (X_4), the health technical personnel (X_5), the education level (X_6) (Average number of students per full-time teacher), the urbanization rate (X_7) and the social security coverage rate (X_8) (The proportion of urban workers insured by basic old-age insurance to the total registered population) are taken as the corresponding comparison sequences. The above eight factors, which cover the economy, government input, social services, health and education resources, and urbanization level, are closely related to population aging. Among them, GDP, per capita disposable income and total exports can reflect regional economic strength and living standards. Public budget expenditure and social security coverage rate can reflect government investment in old-age and medical services. Health personnel and education level represent health security and human capital. Urbanization rate reflects changes in demographics and lifestyles. Then, the grey relational degrees of panel data between the reference sequence X_0 and the corresponding comparison sequences X_1、X_2、X_3、X_4、X_5、X_6、X_7、X_8 is calculated respectively. The corresponding panel data of 9 sequences are shown in Tables 5, 6, 7, 8, 9, 10, 11, 12 and 13.

Table 5 Number of elderly population in four cities from 2016 to 2023 (Unit: 10,000 people)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	90.76	99.01	105.16	107.58	127.59	136.57	144.70	152.87
Suzhou	110.31	115.32	130.56	138.45	158.58	168.31	178.16	185.49
Nantong	140.22	147.00	153.72	165.80	175.13	182.77	190.69	196.82
Xuzhou	101.26	103.35	108.14	112.33	133.71	140.60	146.96	150.86

Table 6 Gross domestic product of four cities from 2016 to 2023 (Unit: 100 million yuan)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	10,819.14	11,894.00	13,009.17	14,045.15	14,782.95	16,290.13	16,776.32	17,421.40
Suzhou	15,445.26	16,997.47	18,263.48	19,264.80	20,180.45	23,168.21	23,805.29	24,653.37
Nantong	7151.69	8034.07	8753.23	9369.39	10,018.31	10,946.95	11,309.02	11,813.27
Xuzhou	5809.81	6333.50	6710.36	7053.35	7284.77	8007.44	8412.38	8900.44

Table 7 Per capita disposable income of urban households in four cities from 2016 to 2023 (Unit: yuan)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	49,997	54,538	59,308	64,372	67,553	73,593	76,643	79,858
Suzhou	54,341	58,806	63,481	68,629	70,966	76,888	79,537	82,989
Nantong	39,247	42,756	46,321	50,217	52,484	57,289	59,605	62,512
Xuzhou	28,421	30,987	33,586	36,215	37,523	40,842	42,610	44,796

Table 8 Total value of exports of four cities from 2016 to 2023 (Unit: 100 million yuan)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	2061.87	2246.03	2609.79	3308.34	3398.90	3989.90	3827.90	3333.12
Suzhou	11,422.10	12,214.69	14,250.24	13,403.24	12,941.49	14,875.76	15,475.04	15,081.59
Nantong	1603.22	1627.53	1753.66	1737.17	1792.61	2263.39	2350.38	2289.69
Xuzhou	365.64	413.38	668.86	787.83	865.30	1050.29	1111.96	997.42

Table 9 General public budget expenditure in four cities from 2016 to 2023 (Unit: 100 million yuan)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1173.84	1354.09	1532.72	1658.07	1754.46	1817.88	1828.69	1838.70
Suzhou	1617.11	1771.47	1952.71	2141.45	2263.51	2583.70	2588.57	2621.28
Nantong	749.22	810.08	877.18	972.64	1080.62	1122.22	1147.22	1180.93
Xuzhou	797.99	827.33	880.86	882.21	958.19	1004.40	1031.82	1056.90

Grey relational degree calculation based on panel data

First, the above 9 groups of panel data need to be initialized. Because of the different dimensions of the 9 multidimensional data sequences, the initializing operator is used to process the original data. In this way, 9 groups of dimensionless panel data are obtained, as shown in Table 14, 15, 16, 17, 18, 19, 20, 21 and 22.

Then, after calculating the range and comparing the sizes according to formula (20), $S = 4.11$ and $s = 0$ is obtained. After substituting S and s, the following formula can be obtained:

Table 10 Health technical personnel in four cities from 2016 to 2023 (Unit: 10,000 people)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	7.07	7.61	8.41	9.39	9.96	10.47	10.86	11.27
Suzhou	7.22	7.96	8.52	9.10	9.53	10.10	10.55	11.22
Nantong	4.36	4.56	4.80	5.03	5.33	5.62	5.77	6.06
Xuzhou	5.55	5.75	6.74	7.08	7.32	7.49	7.63	7.82

Table 11 Education level of four cities from 2016 to 2023 (Unit: people)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	14.68	14.43	13.94	13.80	13.73	15.75	15.52	15.48
Suzhou	18.74	18.46	18.87	19.00	18.93	19.52	19.49	18.60
Nantong	19.21	19.79	21.09	19.94	21.24	24.48	25.44	24.40
Xuzhou	17.10	21.40	17.00	17.10	17.50	19.40	19.50	20.00

The Education Level is measured by the average number of students per full-time teacher

Table 12 Urbanization rate of four cities from 2016 to 2023 (Unit: %)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	84.19	84.91	85.22	86.12	86.80	86.90	87.01	87.20
Suzhou	77.79	78.60	79.60	81.58	81.72	81.93	82.12	82.48
Nantong	65.33	67.16	68.42	69.58	70.44	71.20	71.79	72.57
Xuzhou	61.10	62.12	63.16	64.28	65.63	66.19	66.81	67.64

Table 13 Social security coverage rate of four cities from 2016 to 2023 (Unit: %)

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	45.79	45.41	45.54	45.89	46.72	50.83	51.08	50.61
Suzhou	76.77	79.39	81.85	80.48	80.32	81.32	80.51	78.93
Nantong	28.15	28.51	29.95	31.59	22.97	23.66	24.15	24.47
Xuzhou	14.92	17.50	18.58	19.78	20.60	19.00	19.72	20.08

The Social Security Coverage Rate is measured by the proportion of urban workers insured by basic old-age insurance to the total registered population

Table 14 Panel data of the elderly population after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.90	0.98	1.04	1.06	1.26	1.35	1.43	1.51
Suzhou	1.09	1.14	1.29	1.37	1.57	1.66	1.76	1.83
Nantong	1.38	1.45	1.52	1.64	1.73	1.80	1.88	1.94
Xuzhou	1.00	1.02	1.07	1.11	1.32	1.39	1.45	1.49

Table 15 Panel data of gross domestic product after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.86	2.05	2.24	2.42	2.54	2.80	2.89	3.00
Suzhou	2.66	2.93	3.14	3.32	3.47	3.99	4.10	4.24
Nantong	1.23	1.38	1.51	1.61	1.72	1.88	1.95	2.03
Xuzhou	1.00	1.09	1.16	1.21	1.25	1.38	1.45	1.53

Table 16 Panel data of per capita disposable income of urban households after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.76	1.92	2.09	2.26	2.38	2.59	2.70	2.81
Suzhou	1.91	2.07	2.23	2.41	2.50	2.71	2.80	2.92
Nantong	1.38	1.50	1.63	1.77	1.85	2.02	2.10	2.20
Xuzhou	1.00	1.09	1.18	1.27	1.32	1.44	1.50	1.58

Table 17 Panel data for total value of exports after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	5.64	6.14	7.14	9.05	9.30	10.91	10.47	9.12
Suzhou	31.24	33.41	38.97	36.66	35.39	40.68	42.32	41.25
Nantong	4.38	4.45	4.80	4.75	4.90	6.19	6.43	6.26
Xuzhou	1.00	1.13	1.83	2.15	2.37	2.87	3.04	2.73

Table 18 Panel data of general public budget expenditure after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.47	1.70	1.92	2.08	2.20	2.28	2.29	2.30
Suzhou	2.03	2.22	2.45	2.68	2.84	3.24	3.24	3.28
Nantong	0.94	1.02	1.10	1.22	1.35	1.41	1.44	1.48
Xuzhou	1.00	1.04	1.10	1.11	1.20	1.26	1.29	1.32

Table 19 Panel data of health technical personnel after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.27	1.37	1.52	1.69	1.79	1.89	1.96	2.03
Suzhou	1.30	1.43	1.54	1.64	1.72	1.82	1.90	2.02
Nantong	0.79	0.82	0.86	0.91	0.96	1.01	1.04	1.09
Xuzhou	1.00	1.04	1.21	1.28	1.32	1.35	1.37	1.41

$$\gamma_{0n}(m,t) = \frac{0.5 \times 4.11}{\left|x_0(m,t)d - x_n(m,t)d\right| + 0.5 \times 4.11} \tag{24}$$

Through calculation, the distance correlation coefficients are obtained, as shown in Table 23, 24, 25, 26, 27, 28, 29 and 30.

Then, the grey correlation degrees of panel data between the reference sequence X_0 and the comparison sequences $X_n(n = 1, 2, \cdots, 8)$ can be obtained by using formula (21), as follows:

Table 20 Panel data of education level after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.86	0.84	0.82	0.81	0.80	0.92	0.91	0.91
Suzhou	1.10	1.08	1.10	1.11	1.11	1.14	1.14	1.09
Nantong	1.12	1.16	1.23	1.17	1.24	1.43	1.49	1.43
Xuzhou	1.00	1.25	0.99	1.00	1.02	1.13	1.14	1.17

Table 21 Panel data of urbanization rate after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.38	1.39	1.39	1.41	1.42	1.42	1.42	1.43
Suzhou	1.27	1.29	1.30	1.34	1.34	1.34	1.34	1.35
Nantong	1.07	1.10	1.12	1.14	1.15	1.17	1.17	1.19
Xuzhou	1.00	1.02	1.03	1.05	1.07	1.08	1.09	1.11

Table 22 Panel data of social security coverage rate after initialization

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	3.07	3.04	3.05	3.08	3.13	3.41	3.42	3.39
Suzhou	5.15	5.32	5.49	5.39	5.38	5.45	5.40	5.29
Nantong	1.89	1.91	2.01	2.12	1.54	1.59	1.62	1.64
Xuzhou	1.00	1.17	1.25	1.33	1.38	1.27	1.32	1.35

Table 23 Distance correlation coefficient $\gamma_{01}(m,t)$ between number of elderly population and gross domestic product

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.68	0.66	0.63	0.60	0.62	0.59	0.58	0.58
Suzhou	0.57	0.53	0.53	0.51	0.52	0.47	0.47	0.46
Nantong	0.93	0.97	0.99	0.99	1.00	0.96	0.97	0.96
Xuzhou	1.00	0.97	0.96	0.95	0.97	1.00	1.00	0.98

Table 24 Distance correlation coefficient $\gamma_{02}(m,t)$ between number of elderly population and per capita disposable income of urban households

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.69	0.66	0.63	0.65	0.62	0.62	0.61	1.00
Suzhou	0.69	0.69	0.66	0.69	0.66	0.66	0.65	1.00
Nantong	0.98	0.95	0.94	0.95	0.91	0.91	0.89	1.00
Xuzhou	0.97	0.95	0.93	1.00	0.98	0.98	0.96	1.00

Table 25 Distance correlation coefficient $\gamma_{03}(m,t)$ between number of elderly population and total value of exports

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.30	0.28	0.25	0.20	0.20	0.18	0.19	0.21
Suzhou	0.06	0.06	0.05	0.06	0.06	0.05	0.05	0.05
Nantong	0.41	0.41	0.39	0.40	0.39	0.32	0.31	0.32
Xuzhou	1.00	0.95	0.73	0.66	0.66	0.58	0.56	0.62

Table 26 Distance correlation coefficient $\gamma_{04}(m,t)$ between number of elderly population and general public budget expenditure

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	1.04	1.14	1.24	1.27	1.30	1.30	1.25	1.21
Suzhou	0.65	0.62	0.59	0.56	0.57	0.52	0.53	0.54
Nantong	1.08	1.06	1.10	1.08	1.11	1.14	1.19	1.21
Xuzhou	1.00	0.99	0.98	1.00	0.94	0.94	0.93	0.93

Table 27 Distance correlation coefficient $\gamma_{05}(m,t)$ between number of elderly population and health technical personnel

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.95	0.96	1.00	0.97	0.97	0.96	0.97	0.96
Suzhou	0.84	0.82	0.81	0.78	0.82	0.81	0.81	0.80
Nantong	0.87	0.87	0.83	0.82	0.77	0.76	0.74	0.74
Xuzhou	1.00	0.99	0.93	0.93	1.00	0.98	0.96	0.96

Table 28 Distance Correlation Coefficient $\gamma_{06}(m,t)$ between number of elderly population and education level

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.98	0.94	0.90	0.89	0.82	0.83	0.80	0.77
Suzhou	1.00	0.97	0.92	0.89	0.82	0.80	0.77	0.73
Nantong	0.89	0.87	0.88	0.81	0.81	0.85	0.84	0.80
Xuzhou	1.00	0.90	0.97	0.95	0.87	0.89	0.87	0.87

Table 29 Distance correlation coefficient $\gamma_{07}(m,t)$ between number of elderly population and urbanization rate

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.81	0.83	0.85	0.86	0.93	0.97	1.00	0.96
Suzhou	0.92	0.93	0.99	0.98	0.90	0.86	0.83	0.81
Nantong	0.87	0.85	0.84	0.80	0.78	0.76	0.74	0.73
Xuzhou	1.00	1.00	0.98	0.97	0.89	0.87	0.85	0.84

Table 30 Distance correlation coefficient $\gamma_{08}(m,t)$ between number of elderly population and social security coverage rate

Year	2016	2017	2018	2019	2020	2021	2022	2023
Nanjing	0.49	0.50	0.51	0.51	0.52	0.50	0.51	0.52
Suzhou	0.34	0.33	0.33	0.34	0.35	0.35	0.36	0.37
Nantong	0.80	0.82	0.81	0.81	0.92	0.90	0.89	0.87
Xuzhou	1.00	0.93	0.92	0.90	0.97	0.95	0.94	0.93

$$\gamma_{01} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{01}(m,t) = 0.768,$$
$$\gamma_{02} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{02}(m,t) = 0.827,$$
$$\gamma_{03} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{03}(m,t) = 0.690,$$
$$\gamma_{04} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{04}(m,t) = 0.969,$$
$$\gamma_{05} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{05}(m,t) = 0.887,$$
$$\gamma_{06} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{06}(m,t) = 0.871,$$
$$\gamma_{07} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{07}(m,t) = 0.880,$$
$$\gamma_{08} = \frac{1}{8\times4}\sum_{m=1}^{8}\sum_{t=1}^{4}\gamma_{08}(m,t) = 0.662.$$

During 2016–2023, except for the correlation degree of total value of exports and social security coverage rate, which is close to 0.7, the correlation degrees between all other factors and the number of elderly population are all greater than 0.7. From a comprehensive perspective, almost all of the above eight influencing factors have a significant impact on the number of elderly people. Among them, the correlation degree of general public budget expenditure is the highest, indicating that the government's input in public expenditure has the most significant impact on the regional aging process. Secondly, the high correlation of per capita disposable income of urban households indicates that the economic strength and consumption level of residents reflect and influence the aging phenomenon to a certain extent. The high correlation of the health technical personnel indicates that the sufficient and distribution of medical and health resources plays a key supporting role in the health management and elderly care services of the elderly population. The high correlation of education level suggests that higher education level may improve the health awareness and lifestyle of the elderly, thus influencing the aging trend. The high correlation of urbanization rate indicates that the urbanization process plays an important role in promoting demographic changes, gathering the elderly population, or improving elderly care services. Finally, the correlation degrees between total value of exports, social security coverage rate and the number of elderly population are relatively low. The correlation degree of total value of exports is close to 0.7, indicating that the economic activity of foreign trade is indirectly related to regional economic development and aging. The correlation degree of social security coverage rate is similar, indicating that its coverage is related to the size of the elderly population, and the effectiveness of security may regulate the aging trend.

Discussion

Characteristics analysis of population aging trend in Jiangsu Province

Based on the prediction and analysis of the population aging trend in Jiangsu Province and the factor analysis results based on the GRA of panel data, it can be concluded that the future population aging in Jiangsu Province will present the following main characteristics:

(1) **The degree of aging continues to deepen.** The proportion of people aged 60 and above and 65 and above in Jiangsu Province will continue to rise, which is reflected in the continuous expansion of the absolute number of elderly people, but also in its proportion in the total population continues to rise. In recent years, the elderly population dependency ratio in Jiangsu Province has been significantly higher than the national average (for example, the province's elderly dependency ratio will reach 27.14% in 2023), reflecting that social pension, medical and public services will face greater pressure. In the future, under the dual effects of continued low fertility rate and extended life expectancy, the problem of "getting old before getting rich" may be further aggravated, which requires a balanced development of economic growth and elderly care service system in policy formulation.

(2) **Obvious regional differentiation.** There are obvious differences in the degree of population aging among regions in Jiangsu Province. The aging level in central Jiangsu and some northern Jiangsu areas is significantly higher than that in southern Jiangsu, and this spatial differentiation may be further strengthened in the future. Factors such as regional economic development level, urban–rural structure difference and population flow together lead to

significant heterogeneity in the demand for elderly care resource supply, medical services and social security policies in different regions. Therefore, it is particularly necessary to build a regional differentiated and accurate pension policy system.

(3) **Complex multi-cause dynamic interaction effects.** The factor analysis based on the grey correlation model of panel data reveals that the population aging trend in Jiangsu Province is not only driven by basic demographic variables (such as the decline of fertility rate and the extension of life expectancy), but also closely related to multiple factors such as regional economic development level, medical and health conditions, urban and rural population flow, and the perfection of social security system. This mechanism of multi-cause interweaving and dynamic evolution makes the aging trend have strong uncertainty and regional characteristics.

Suggestions on actively respond to the population aging

Based on the FGM(1,1) model and GRA based on panel data, this paper puts forward several policy recommendations to proactively tackle the challenges associated with an aging population. These recommendations aim to alleviate the potential pressures on elderly care and social security systems caused by population structural imbalances, thereby facilitating dynamic equilibrium in population structure and fostering sustainable societal development.

(1) **Adjusting the fertility policy to optimize the population structure.** According to the prediction results of the FGM(1,1) model, the population aged 65 and above in Jiangsu Province will increase significantly in the next ten years. It is estimated that by the end of 2033, the population of this group will reach 23.5733 million, and the aging coefficient will continue to rise, indicating that the risk of population structure imbalance will further intensify. To address this severe challenge, it is suggested that the fertility policy be adjusted in a timely manner based on the expected aging trend to promote the long-term optimization of the population structure. Specifically, policymakers should gradually relax fertility restrictions and effectively reduce the cost of childbirth through tax breaks and child-rearing subsidies to stimulate the fertility willingness of couples of childbearing age. At the same time, attention should also be paid to the potential impact of low fertility rates on future labor supply, and differentiated policies should be implemented in different regions based on local conditions to build a stable institutional guarantee and promote the dynamic balance and sustainable development of the population structure.

(2) **Strengthen public finance and medical security investment.** Empirical research shows that general public budget expenditure and the number of health technicians have a significant impact on population aging in Jiangsu Province. Therefore, strengthening public finance and medical security investment is the fundamental guarantee for addressing the challenges of aging. To this end, it is recommended that the government further optimize the structure of fiscal expenditure and prioritize ensuring the supply of funds in the fields of elderly care services and medical security. Specific measures include setting up special funds and improving the mechanism of fiscal transfer payments to ensure the long-term stable operation of the elderly care service system. At the same time, efforts should be made to increase the training of professional talents in geriatric medicine and nursing. And actively explore diversified medical service models such as home-based, community-based and remote diagnosis and treatment, so as to comprehensively improve the quality of medical services and protect the health rights and interests of the elderly population.

(3) **Build an aging-friendly urban system and improve the community elderly care service network.** Given the close connection between the urbanization process and population aging, building an aging-friendly urban system and improving the community elderly care service network have become key measures to enhance the quality of life for the elderly. It is suggested that the concept of aging-friendly design be fully implemented in urban planning and construction, the layout of barrier-free public facilities be optimized, the elderly care service functions of communities be strengthened, and the effective connection between home-based care and institutional care be promoted. In addition, by encouraging public–private partnership models and attracting social capital to participate in the construction and operation of elderly care facilities, a multi-level and sustainable elderly care service system can be formed, achieving rational allocation and efficient utilization of resources.

(4) **Enhance the educational attainment of the entire population and the income of residents.** Considering that educational attainment and the per capita disposable income of urban residents have a certain impact on the aging process, enhancing the educational attainment of the entire population and the income of residents is regarded as a long-term strategy for achieving healthy aging and optimizing

the population structure. To this end, it is suggested that the government implement a lifelong education and elderly health knowledge popularization project to enhance the self-healthcare ability of the elderly group. At the same time, targeted policies to support middle-aged and young families should be introduced to improve the economic foundation of families and fundamentally alleviate the potential pressure on elderly care and social security caused by future population structure imbalance.

Conclusions and future work

Conclusions and significance

With the continuous development of society, China is facing an increasingly serious problem of population aging. This phenomenon has triggered a series of policy adjustments, including changes in the structure of the labor force, strengthening of public medical construction and improving elderly care services. In this paper, Jiangsu Province, where the problem of population aging is particularly prominent, is taken as an example, and the trend of population aging in Jiangsu Province is predicted by using the FGM(1,1) model. The results show that in the next ten years, the number of elderly population and the aging coefficient of Jiangsu Province will continue to increase. At the same time, through the GRA based on panel data, this paper deeply discusses the related factors affecting the aging population in Jiangsu Province. The study found that the general public budget expenditure, health technical personnel, urbanization rate and other factors have a significant impact on the growth of the elderly population. The comprehensive application of FGM(1,1) model and GRA based on panel data is helpful to understand the population aging problem in Jiangsu Province more comprehensively and deeply.

This study is of great significance to actively cope with the aging population in China. First of all, the accurate prediction of the development trend of the aging population provides a scientific and forward-looking reference for the government and relevant decision-making bodies. It is helpful to plan the construction of elderly care service facilities in advance, rationally adjust the pension system, formulate appropriate medical security policies, and more effectively meet the needs of the future elderly population. Secondly, this paper reveals the level of economic development, medical and health conditions, rural–urban population flow and other key factors affecting population aging. This deepens the understanding of the complexity of population aging and helps to accurately identify and solve the main problems that hinder active aging. Finally, this paper expands the research of aging in theory and practice. FGM(1,1) model has a unique advantage in dealing with uncertainty and complexity, and GRA is helpful to reveal the degree of correlation and influence among different factors. The combination of the two not only improves the prediction accuracy, but also provides a new technical means for the study of aging problems and enricues the methodology of aging research.

Future work

The FGM(1,1) model and GRA method adopted in this study still have some limitations. First of all, FGM(1,1) model assumes that the data has certain regularity, but in practice, unexpected events and nonlinear changes may affect the prediction results. GRA focuses on the correlation between factors and fails to fully consider the complexity of causality. Second, this study relies on publicly available statistics, and lags or missing data may affect the accuracy of the results. Furthermore, FGM(1,1) model is suitable for systems with small samples and high uncertainty, but its applicability and prediction accuracy may be limited when dealing with large-scale and high-dimensional data.

Future works may consider introducing more external factors, such as economic policies and international environment, to build more complex multivariate forecasting models. At the same time, combined with advanced methods such as machine learning, the parameter estimation and prediction performance of FGM(1,1) model are optimized. Secondly, more comprehensive and high-quality relevant data, especially micro-data on the influence factors of aging, should be collected to enhance the explanatory power and prediction ability of the model. In addition, regional comparative studies are carried out to explore the commonalities and differences of population aging in different regions, so as to provide a broader reference for policy making.

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Authors' contributions

XG was involved in the conception and design, acquisition of data, analysis, and interpretation of data, drafting and revising manuscript; YW and YW contributed to the study design, data analysis, drafting and revising of the manuscript; HS participated in the study design, data analysis, drafting of the manuscript; YY contributed to the design, planning, coordination, and revision of manuscript; YF was involved in the study design, data interpretation, analysis, and revision of the manuscript. The final manuscript had been read and approved by all authors.

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Data availability

All data generated or analysed during this study are included in this published article. And the datasets used and analysed during the current study are available in http://tj.jiangsu.gov.cn, http://wjw.jiangsu.gov.cn.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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