Original Article

MENG Na^1,2^, Aifeire ABEIBAO^1^, WU Pei^1,3^, LIU Qin^1^, HUANG Mengsi^1^, YOU Shuping^1,2*^

2026-06-25

ChinaRxiv

Abstract

Background As population aging accelerates in China, the issue of old-age care for rural older adults has become increasingly prominent, and old-age care vulnerability has become an important indicator for measuring the quality of old-age care. Objective To identify the dynamic trajectories of family-based old-age care vulnerability among rural older adults in Xinjiang and predict its development level over the next 6 years, providing a theoretical basis for formulating rural old-age care service policies in Xinjiang. Methods The data were derived from the longitudinal survey "Old-Age Care Status of Rural Older Adults in Xinjiang" conducted by the research team from January 2017 to April 2025 in rural areas of Urumqi, Xinjiang. The survey used a multistage stratified random sampling method, with rural older adults aged $ $60 years in Urumqi as the study population. The baseline survey was completed from January to June 2017, and follow-up surveys were conducted every 2 years from January to June in 2019, 2021, and 2023, and from January to April in 2025. A total of 1 133 valid samples were ultimately included. The questionnaire covered residents' general characteristics (age, sex, marital status, and main economic source for old-age care) and the Family-Based Old-Age Care Vulnerability Questionnaire. The entropy weight-TOPSIS method was used to calculate the family-based old-age care vulnerability index, the group-based trajectory model (GBTM) was used to fit heterogeneous trajectories of changes in the vulnerability index, and the grey prediction model GM(1,1) was used to predict the level of old-age care vulnerability from 2026 to 2031. Results From 2017 to 2025, the family-based old-age care vulnerability index among rural older adults in Xinjiang showed an overall slow upward trend. The GBTM model fitted the dynamic trajectories into three categories: a low-level stable group with 453 cases (39.98%), a medium-level persistent group with 521 cases (45.98%), and a high-level rising group with 159 cases (14.03%). The grey prediction model showed that the predicted vulnerability index values for the low-level stable group, medium-level persistent group, and high-level rising group were 0.098, 0.108, and 0.118 in 2027; 0.186, 0.202, and 0.219 in 2029; and 0.405, 0.441, and 0.480 in 2031, respectively. Conclusion The family-based old-age care vulnerability of rural older adults in Xinjiang will remain at a relatively high level and continue to increase over the next 6 years. Attention should be paid to the individual characteristics of rural older adults and differences in old-age care resources, and more precise old-age care strategies should be formulated.

Full Text

Original Article

The Identification of Dynamic Trajectories and Short-Term Prediction of Family-based Eldercare Vulnerability among Rural Elderly Households in Xinjiang

MENG Na[1,2], Aifeire ABEIBAO[1], WU Pei[1,3], LIU Qin[1], HUANG Mengsi[1], YOU Shuping^1,2*^

1. 830017 Urumqi, Xinjiang Uygur Autonomous Region, School of Nursing, Xinjiang Medical University

2. 830017 Urumqi, Xinjiang Uygur Autonomous Region, Xinjiang Regional Population Disease and Health Care Research Center

3. 831100 Changji, Xinjiang Uygur Autonomous Region, Department of Cardiology, Changji Branch of the First Affiliated Hospital of Xinjiang Medical University
   * Corresponding author: YOU Shuping, Professor/Doctoral supervisor; E-mail: youshupin@163.com

【Abstract】 **Background** With the acceleration of population aging in China, the issue of eldercare for rural older adults has become increasingly prominent, and eldercare vulnerability has become an important indicator for measuring the quality of eldercare. **Objective** To identify the dynamic change trajectories of family-based eldercare vulnerability among rural older adults in Xinjiang and predict its level of development over the next 6 years, thereby providing a theoretical basis for formulating rural eldercare service policies in Xinjiang. **Methods** The study data were derived from the research group' s longitudinal survey, "Eldercare Status of Rural Older Adults in Xinjiang," conducted in rural areas of Urumqi, Xinjiang, from January 2017 to April 2025. The survey used multistage stratified random sampling, taking rural residents aged $ $60 years in Urumqi as the study population. The baseline survey was completed from January to June 2017, and follow-up surveys were conducted every 2 years from January to June 2019, January to June 2021, January to June 2023, and January to April 2025. A total of 1,133 valid samples were ultimately included. The questionnaire covered residents' general information—including age, sex, marital status, and main economic source for eldercare—as well as a family-based eldercare vulnerability questionnaire. The entropy-weight TOPSIS method was used to calculate the family-based eldercare vulnerability index; a group-based trajectory model (GBTM) was used to fit heterogeneous change trajectories of the vulnerability index; and the grey prediction model GM(1,1) was used to predict eldercare vulnerability levels from 2026 to 2031. **Results** From 2017 to 2025, the overall family-based eldercare vulnerability index among rural older adults in Xinjiang showed a slow upward trend. The GBTM model fitted the dynamic change trajectories into 3 categories: a low-level stable group of 453 cases (39.98%), a medium-level persistent group of 521 cases (45.98%), and a high-level increasing group of 159 cases (14.03%). The grey prediction model showed that the predicted vulnerability index values for the low-level stable group, medium-level persistent group, and high-level increasing group were 0.098, 0.108, and 0.118, respectively, in 2027; 0.186, 0.202, and 0.219, respectively, in 2029; and 0.405, 0.441, and 0.480, respectively, in 2031. **Conclusion** Family-based eldercare vulnerability among rural older adults in Xinjiang will remain at a relatively high level and continue to rise over the next 6 years. Attention should be paid to the individual characteristics of rural older adults and the heterogeneity of eldercare resources, and more precise eldercare strategies should be formulated.

【Keywords】 family-based eldercare vulnerability; rural health; GBTM model; grey prediction model; cohort study; Xinjiang

【Chinese Library Classification No.】 R193 【Document Code】 A DOI: 10.12114/j.issn.1007-9572.2025.0356

The Identification of Dynamic Trajectories and Short-Term Prediction of Family-based Eldercare Vulnerability among Rural Elderly Households in Xinjiang

MENG Na[1,2], ABEIBAO Aifeire[1], WU Pei[1,3], LIU Qin[1], HUANG Mengsi[1], YOU Shuping^1,2*^

1.School of Nursing, Xinjiang Medical University, Urumqi 830017, China
2.Xinjiang Regional Population Disease and Health Care Research Center, Urumqi 830017, China
3.Department of Cardiology, Changji Branch of the First Affiliated Hospital of Xinjiang Medical University, Changji 831100, China
* Corresponding author: YOU Shuping, Professor/Doctoral supervisor; E-mail: youshupin@163.com

【Abstract】 **Background** With the acceleration of population aging in China, the issue of elderly care in rural areas has become increasingly prominent, and elderly care vulnerability has become an important indicator for measuring the quality of elderly care. **Objective** To identify the dynamic change trajectories of family-based elderly care vulnerability among rural elderly in Xinjiang and to predict its development level over the next six years, so as to provide a theoretical basis for formulating rural elderly care service policies in Xinjiang. **Methods** Data were obtained from the longitudinal survey titled "Elderly Care Status of

Fund projects: National Social Science Fund of China (24BSH046); Social Science Fund Project of Xinjiang Uygur Autonomous Region (2023BSH066)

Rural Elderly in Xinjiang" conducted by the research team in rural areas of Urumqi, Xinjiang, from January to June 2017 to April 2025. A multistage stratified random sampling method was adopted to select rural residents aged ≥ 60 in Urumqi as the study subjects. The baseline survey was completed from January to June 2017, followed by follow-up surveys every two years in January–June 2019, January–June 2021, January–June 2023, and January–April 2025, with a total of 1 133 valid samples ultimately included. The survey contents included general information (age, gender, marital status, financial sources for elderly care, etc.) and the family-based elderly care vulnerability questionnaire. The entropy-weight TOPSIS method was used to calculate the family-based elderly care vulnerability index; the group-based trajectory model (GBTM) was applied to fit the heterogeneous trajectories of the vulnerability index; and the grey prediction model GM (1, 1) was employed to predict the level of elderly care vulnerability from 2026 to 2031. **Results** From 2017 to 2025, the family-based elderly care vulnerability index of rural elderly in Xinjiang showed an overall slow upward trend. The GBTM identified three distinct trajectory groups: a low-level stable group (V1) with 453 cases (39.98%), a medium-level persistent group (V2) with 521 cases (45.98%), and a high-level rising group (V3) with 159 cases (14.03%). The grey prediction model revealed that the predicted vulnerability index values for the V1, V2, and V3 groups would be 0.098, 0.108, and 0.118 in 2027; 0.186, 0.202, and 0.219 in 2029; and 0.405, 0.441, and 0.480 in 2031, respectively. **Conclusion** The family-based elderly care vulnerability of rural elderly in Xinjiang will remain at a relatively high level and show a continuous upward trend over the next six years. Attention should be paid to the characteristics of the rural elderly themselves and the disparities in elderly care resources, so as to formulate more precise elderly care strategies.

【Key words】 Family-based eldercare vulnerability; Rural health; GBTM model; Grey forecasting model; Cohort study; Xinjiang

Since the beginning of the 21st century, population aging has become a global and sustained structural demographic transition, profoundly affecting the allocation of health resources and population health outcomes[1]. According to

WHO projections, by 2050 the proportion of China' s population aged 60 years and above will exceed 30%, making China one of the countries with the fastest growth in population aging worldwide[2]. The "*Healthy China 2030*" *Planning Outline* proposes promoting a strategy of healthy aging, relying on improving the elderly health service system and consolidating the old-age security system to actively respond to the challenges of population aging[3]. The core of healthy aging is to maintain intact physiological, psychological, and social functions among older adults and to reduce the risks of chronic disease onset and disability[4]. China is a typical country that is "aging before becoming rich" ; implementing the healthy aging strategy therefore requires both improving medical and health services for older adults and continuously strengthening old-age security for them.

Vulnerability is an inherent attribute whereby an individual or system, because of sensitivity to internal and external risks and insufficient resistance and post-disaster recovery capacity, is prone to losing its original functions and steady state after being struck by risks[5]. Rural older adults in China are a population with a high incidence of vulnerability; health status, socioeconomic conditions, accessibility of medical care, and population mobility are all risk factors inducing vulnerability in elderly care[6–8]. Precisely managing and controlling, and delaying the worsening of vulnerability among rural older adults is of great practical significance for implementing healthy aging and advancing the construction of a Healthy China. Existing studies related to elderly care vulnerability among older adults mostly adopt cross-sectional designs and focus on analyses of influencing factors[9], development of assessment tools[10], and comparisons of provincial and regional differences in vulnerability[10–11]. However, longitudinal trajectory studies targeting rural older adults remain relatively scarce, and few studies have predicted the long-term evolutionary patterns of vulnerability.

Data from the Seventh National Population Census show that Xinjiang has 2.917 million older adults aged 60 years and above, accounting for 11.28% of the total population of the region[12]; it is estimated that by 2050 this group will rise to 33.19%, approximately one-third of the total population[13]. The development of elderly care in rural Xinjiang faces a dual dilemma: first, there is a shortage in the supply of medical and elderly care resources, and the vulnerability risk among rural older adults is markedly higher than that among urban residents[14]; second, its unique geographical location, diverse folk customs, and seasonal population mobility have generated localized mechanisms for the formation of elderly care vulnerability. At the present stage, research on elderly care vulnerability is mostly limited to static assessment and cannot characterize the dynamic evolution of vulnerability. A small number of dynamic studies have been conducted based on macro-level population data, but they fail to incorporate key micro-level indicators such as household livelihood capital, making it difficult to reflect their critical role in the quality of elderly care. Meanwhile, heterogeneity within the older population remains unclear, and the population characteristics associated with worsening or improvement of vulnerability cannot be clarified, leaving relevant policies without targeted evidence for stratified interventions.

This research group has previously established an evaluation indicator system for elderly care vulnerability among rural older adults in Xinjiang[15], confirming that elderly care vulnerability among different individuals differentiates over time into distinct developmental trajectories. Therefore, scientifically predicting the future evolutionary trends of elderly care vulnerability is practically necessary. Building on the existing research foundation, this study innovatively applies a coupled group-based trajectory model (GBTM) and grey prediction model GM (1, 1) to improve the methodological support for trend prediction: GBTM relies on finite mixture models to classify potential heterogeneous subgroups[16], has concise parameters, and yields results that are easy to interpret for clinical and policy purposes; GM (1, 1) is adept at handling small-sample, poor-information data and can effectively compensate for research limitations caused by missing longitudinal follow-up data[17]. This study analyzes the evolutionary patterns of family-based elderly care vulnerability among rural older adults in Xinjiang and predicts the trend of change over the next six years, providing forward-looking theoretical reference and practical evidence for optimizing rural elderly care services in Xinjiang and improving the regional old-age security system.

1 Objects and Methods

1.1 Study Subjects

This study was jointly funded by a National Social Science Fund project and a Xinjiang Uygur Autonomous Region Social Science Fund project. The data were derived from the research group's longitudinal survey on the "Elderly Care Status of Rural Older Adults in Xinjiang" [15,18]. The baseline survey was conducted from January to June 2017 (T0) using multistage stratified random sampling. The specific sampling method was as follows: in the first stage, Urumqi City was randomly selected as the survey

as the study area; in the second stage, the rural areas of Urumqi City are mainly distributed in 3 towns and 3 townships of Urumqi County. According to the population proportion of each township/town, 8–9 administrative villages were selected from each town and 3–4 administrative villages from each township, for a total of 36 villages. In the third stage, 45–50 older adults were randomly selected from each village. The study participants were followed up once every 2 years, with 4 rounds of follow-up completed. The follow-up periods were, in sequence, January–June 2019 (T1), January–June 2021 (T2), January–June 2023 (T3), and January–April 2025 (T4). Inclusion criteria: (1) having rural household registration in Urumqi County; (2) age $ $60 years; (3) voluntarily participating in the survey and signing informed consent. Exclusion criteria: poor physical condition, cognitive impairment or psychiatric disease, and inability to cooperate in completing the survey. A total of 1,443 study participants were enrolled at baseline; 310 were lost to follow-up during the follow-up period, and 1,133 valid study participants were ultimately included. The follow-up process of the study participants is shown in Figure 1. This study was reviewed and approved by the Ethics Committee of Xinjiang Medical University (approval No.: XJYKDXR20231208001).

1.2 Data collection

Data were collected by questionnaire survey. The data relevant to this study included two parts: (1) general demographic information, such as age, sex, marital status, and main economic source for old-age support. (2) Survey of family-based old-age care vulnerability: the evaluation indicator system for family-based old-age care vulnerability among rural older adults previously constructed by the research group was used, covering 3 dimensions—exposure, sensitivity, and adaptive capacity—with a total of 34 indicators (Figure 2). On this basis, a questionnaire was developed; the test-retest reliability of the questionnaire was 0.862[13]. The questions and option settings of the questionnaire referred to relevant items in the China Health and Retirement Longitudinal Study (CHARLS) questionnaire. Values were assigned in three ways: dichotomous variables were assigned values of 0 and 1; continuous variables used their actual values; and ordered multicategorical variables were scored from low to high as 1-5 points, respectively (the two indicators of activities of daily living and sleep quality were scored 1-4 points)[15].

Flowchart text in Figure 1:

- **T0: Baseline survey** (*n*=1,443)
  - Excluded (*n*=43):
    (1) unable to make contact (*n*=24); (2) missed follow-up due to relocation, going out, and other reasons (*n*=18); (3) death (*n*=1)
- **T1: First follow-up** (*n*=1,400)
  - Excluded (*n*=76):
    (1) unable to make contact (*n*=46); (2) missed follow-up due to relocation, going out, and other reasons (*n*=23); (3) death (*n*=7)
- **T2: Second follow-up** (*n*=1,324)
  - Excluded (*n*=103):
    (1) unable to make contact (*n*=77); (2) missed follow-up due to relocation, going out, and other reasons (*n*=21); (3) death (*n*=5)
- **T3: Third follow-up** (*n*=1,221)
  - Excluded (*n*=88):
    (1) unable to make contact (*n*=57); (2) missed follow-up due to relocation, going out, and other reasons (*n*=29); (3) death (*n*=2)
- **T4: Fourth follow-up** (*n*=1,133)

Figure 1 Flowchart of follow-up for study subjects

1.3 Statistical methods

Mplus 8.3, MATLAB R2024A, and SPSS 29.0 statistical software were used for data collation and analysis. Samples with a missing rate >20% were excluded, and the remaining missing data were supplemented using multiple imputation[19]. Count data were expressed as relative numbers; normally distributed measurement data were expressed as $(\bar{x} \pm s)$; and non-normally distributed measurement data were expressed as $M(P_{25}, P_{75})$. Intergroup comparisons of count data were performed using the χ^2 test, and intergroup comparisons of non-normally distributed measurement data were performed using the Kruskal-Wallis H test. $P < 0.05$ was considered to indicate a statistically significant difference.

For the original values of the 34 indicators in the survey of family-based old-age care vulnerability among the respondents, the range method was used for standardization; the entropy weight method was used to calculate indicator weights; and the TOPSIS method was used to calculate the family-based old-age care vulnerability index. Taking the old-age care vulnerability index as the evaluation indicator, a GBTM model was constructed to analyze the changing trend of family-based old-age care vulnerability among rural older adults in Xinjiang and to determine trajectory categories and characteristics. The grey prediction model GM(1, 1) was used to predict the changing trend of the vulnerability index from 2026 to 2031.

1.3.1 Construction of the entropy weight-TOPSIS model

The entropy weight method is an objective weighting method that determines weight coefficients by quantifying the degree of variation of each evaluation indicator, thereby avoiding bias from subjective weighting. In this method, the entropy value represents the degree of dispersion of an indicator; the smaller the entropy value, the greater the dispersion of the indicator, and the greater the influence of that indicator on the comprehensive evaluation (i.e., its weight)[20]. The TOPSIS method is a ranking method that approximates the ideal value. It ranks evaluation objects by calculating their relative closeness C_i to the positive and negative ideal solutions. This method first calculates the weighted score of each evaluation object for each indicator, and then obtains the relative closeness C_i of each evaluation object to the positive ideal solution[16]. The old-age care vulnerability index is the result of the combined effects of exposure, sensitivity, and coping capacity. A higher old-age care vulnerability index indicates a more obvious unstable state among older adults when they encounter welfare losses or fall into difficulties in old-age care. In this study, the entropy weight-TOPSIS method was used to comprehensively calculate the family-based old-age care vulnerability index (C_i value) among rural older adults in Xinjiang. The value range is $(0, 1)$; the larger the C_i value, the higher the family-based old-age care vulnerability.

1.3.2 Construction of the GBTM model

This model adopts a semiparametric trajectory grouping strategy. It assumes that multiple potential trajectories exist in the population, can fit the posterior probability that each individual belongs to different trajectories, and uses the growth trajectory corresponding to the individual' s maximum posterior probability as the basis for grouping, thereby achieving population clustering. This model remedies the shortcomings of traditional growth models in exploring population heterogeneity[21]. Model selection comprehensively considered the following criteria: (1) goodness-of-fit indicators. Model selection was performed based on the Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC), and Akaike information criterion (AIC); the lower their absolute values, the better the model fit. Smaller BIC/aBIC values are preferable, but model complexity and gains must be balanced. (2) Classification accuracy. The model was evaluated based on average posterior probability (AvePP); values closer to 1.00 are better, and this study used 0.70 as the criterion for model acceptability. An entropy value close to 1 indicates excellent classification accuracy, and each

The category distinctions are clear. (3) Model parsimony and practicality. Previous studies suggest that model construction should comprehensively consider explanatory power, complexity, and practicality. To avoid overfitting the data while ensuring that the model can summarize data characteristics in the most concise and practical manner, if an additional subgroup fails to capture a trajectory distinctly different from those of other subgroups, priority should be given to selecting a smaller number of trajectory subgroups[17]. (4) Subgroup sample size. The minimum sample size of each subgroup should account for at least 5% of the total sample. Based on the above criteria, starting with a potential number of categories of "1," the number of categories was gradually increased until the optimal model for fitting the data was determined.

1.3.3 Construction of the gray prediction model

The gray prediction model GM (1, 1) is suitable for short-term prediction in systems with small data volumes and incomplete information[22]. In this study, a GM (1, 1) model was constructed based on the family-based eldercare vulnerability index of rural elderly people in Xinjiang from 2017 to 2025. After the model passed the accuracy and fitting tests, it could be used to predict the changing trend of the vulnerability index from 2026 to 2031. The modeling and testing steps were as follows[23].

Step 1: Grade-ratio test (model applicability judgment). Grade ratio = previous-period value / current-period value. If the grade ratios of the data series all fall within the allowable interval $(e^{-2/n+1}, e^{2/n+1})$ (where e is the natural constant and n is the sample size), this indicates that the data are suitable for constructing a GM (1, 1) model.

Step 2: Model construction and parameter estimation. Accumulative generation was performed on the original data series; a first-order differential equation was established; the development coefficient a and gray action quantity b were estimated; and the predicted value sequence was thereby obtained.

Step 3: Model accuracy test (posterior variance ratio test). The posterior variance ratio C value (the ratio of residual variance to data variance) and the small-error probability P value were calculated. In general, $C < 0.35$ indicates excellent performance and $C < 0.65$ indicates acceptability; $P > 0.95$ indicates excellent performance and $P > 0.80$ indicates acceptability.

Step 4: Model fitting-effect test (residual test). The relative error (absolute residual / original value) and grade-ratio deviation were calculated. The smaller the relative error, the better; generally, a value <20% indicates good fitting. An absolute grade-ratio deviation <0.2 is acceptable.

2 Results

2.1 Basic characteristics of rural elderly people in Xinjiang

Among 1,133 elderly people, the mean age was (69.4 ± 6.3) years; 549 were male (48.45%) and 584 were female (51.55%). A total of 980 participants (86.49%) had an educational level of primary school or below; 264 (23.30%) had no spouse. Regarding ability in daily living, 297 (26.21%) were fully self-care, 479 (42.28%) were basically self-care, 334 (29.48%) were mildly dependent, and 23 (2.03%) were severely dependent. A total of 444 participants (39.19%) had 1 chronic disease, and 396 (34.95%) had $ $2 chronic diseases. In the past year, 284 participants (25.07%) had been hospitalized due to illness. The main economic source for eldercare was subsidies from children/relatives and friends for 749 participants (66.11%), and retirement pension/old-age pension for 228 participants (20.12%).

2.2 Analysis of the eldercare vulnerability index

Among the 34 evaluation indicators, the top 4 by weight were, in order: living status (A9, 20.30%), natural disasters (E3, 17.49%), widowhood (E4, 13.41%), and depression (S8, 12.42%); see Figure 2.

Figure 2. Weight distribution of the 34 indicators in the family-based eldercare vulnerability evaluation index system for rural elderly people

Visible labels in the figure: adaptive capacity, 24.78%; exposure, 42.23%; sensitivity, 32.99%; A9, 20.30%; E2, 5.61%; E3, 17.49%; E4, 13.41%; S3, 8.48%; S8, 12.42%.

Legend: E1, medical expenditure; E2, debt; E3, natural disasters; E4, widowhood; E5, no longer working; E6, caring for grandchildren; S1, self-care ability in daily living; S2, BMI; S3, major disease; S4, number of chronic diseases; S5, hospitalization due to illness; S6, vision; S7, hearing; S8, depression; S9, sleep quality; S10, self-rated health status; S11, life satisfaction; A1, cultivated land area; A2, grassland area; A3, household assets; A4, annual household income; A5, household housing area; A6, educational level; A7, proportion of labor force.

According to the weights of the indicators, the TOPSIS method was used to calculate the eldercare vulnerability indices from the five surveys conducted from 2017 to 2025; the values were 0.117 (0.013, 0.485), 0.131 (0.018, 0.420), 0.138 (0.023, 0.444), 0.149 (0.028, 0.568), and 0.168 (0.029, 0.619), respectively.

2.3 Fitting and selection of the developmental trajectory model for eldercare vulnerability

Using the eldercare vulnerability indices of rural elderly people in Xinjiang at five time points as the observed indicators, GBTM was used for model fitting. As the number of categories increased, the fitting indices AIC, BIC, and $aBIC$ all showed a decreasing trend. The BIC (-18 899.466) and $aBIC$ (-18 988.402) of the 3-category model were significantly better than those of the 2-category model, and the improvement in the 4–5-category models gradually decreased. The Lo-Mendell-Rubin (LMR) test for the 3-category model was significant ($P < 0.001$), supporting that the improvement from 2 categories to 3 categories was statistically significant, whereas the LMR tests for the 4–5-category models were not significant ($P > 0.05$). The Entropy of the 3-category model was 0.968, and the sample proportion of each group was >5%. Therefore, this study determined that the 3-category GBTM was the optimal model; the model-fitting information is shown in Table 1.

Based on the 3 categories fitted by GBTM, the developmental trajectories of eldercare vulnerability among rural elderly people in Xinjiang were formed, as shown in Figure 3. In the V1 group, the initial level (mean intercept) of the family-based eldercare vulnerability index was the lowest ($I = 0.065$, $P < 0.001$); the score tended to remain stable from 2017 to 2023 and increased slightly from 2023 to 2025. The average rate of change (mean slope) from 2017 to 2025 was relatively small ($S = 0.005$, $P < 0.001$) and remained at a relatively low level throughout. Therefore, the V1 group was named the "low-level stable group" ($n = 453$, accounting for 39.98%). In the V2 group, the initial level of the family-based eldercare vulnerability index was intermediate ($I = 0.123$, $P < 0.001$); the average rate of change tended to remain stable from 2017 to 2021 and increased slightly from 2021 to 2025; from 2017 to 2025

Table 1 GBTM model fit indices for the development trajectories of family-based eldercare vulnerability among rural elderly in Xinjiang

Latent classes	K	AIC	BIC	aBIC	Entropy	LMR (P value)	BLRT (P value)	Sample proportion (%)	Sample size (persons)
1	8	−11 089.215	−11 048.356	−11 073.767	-	-	-	1.0	-
2	20	−16 874.160	−16 773.507	−16 837.033	0.998	0.240	<0.001	14.4/85.6	160/973
3	28	−19 040.379	−18 899.466	−18 988.402	0.968	<0.001	<0.001	14.0/46.0/40.0	159/521/453
4	36	−19 423.534	−19 242.359	−19 356.706	0.976	0.159	<0.001	41.3/13.8/[illegible]	468/156/497/12
5	44	−20 023.512	−19 802.076	−19 941.833	0.980	0.188	<0.001	40.8/2.2/[illegible]	[illegible]/44/99

Note: GBTM = group-based trajectory model; AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = adjusted Bayesian information criterion; Entropy = entropy value; LMR = Lo–Mendell–Rubin test; BLRT = bootstrap likelihood ratio test.

The average rate of change (mean slope) showed a slight upward trend (S = 0.011, P < 0.001), but remained at an intermediate level throughout; therefore, the V2 group was named the "moderate-level persistent group" (n = 521, accounting for 45.98%). In the V3 group, the initial level of the family-based eldercare vulnerability index was the highest (I = 0.251, P < 0.001); the average rate of change from 2017 to 2025 increased markedly (S = 0.030, P < 0.001); and the scores were consistently higher than those of the V1 and V2 groups. Therefore, the V3 group was named the "high-level increasing group" (n = 159, accounting for 14.03%), as shown in Table 2.

Table 2 Parameter estimation results of the GBTM model for family-based eldercare vulnerability among rural elderly in Xinjiang

Latent class	Mean: intercept (α)	Mean: slope (β)	Variance: intercept (α)	Variance: slope (β)
Low-level stable group (V1)	0.065^a	0.005^a	<0.001	<0.001
Moderate-level persistent group (V2)	0.123^a	0.011^a	<0.001	<0.001

Latent class	Mean: intercept (α)	Mean: slope (β)	Variance: intercept (α)	Variance: slope (β)
High-level increasing group (V3)	0.251[a]	0.030[a]	<0.001	<0.001

Note: $^{a}P < 0.001$.

Figure 3 Schematic diagram of the GBTM-derived class-specific growth trajectories of the family-based eldercare vulnerability index for rural elderly in Xinjiang

Note: GBTM = group-based trajectory model.

2.4 Comparison of baseline data among elderly persons in different categories who completed follow-up

Comparisons of age, sex, education level, marital status, number of children, frequency of life care, ability in activities of daily living, number of chronic diseases, hospitalization due to illness, and main economic sources for old-age support among elderly persons in different categories showed statistically significant differences ($P < 0.05$), as shown in Table 3.

2.5 Interpretation of results from the grey prediction model

GM(1,1) models were constructed separately for the low-level stable group, moderate-level persistent group, and high-level increasing group. The results of the level-ratio test showed that the level-ratio test values for the three groups all fell within the admissible interval $[0.751, 1.331]$, indicating that the data were suitable for constructing GM(1,1) models (Table 4). The model accuracy test results showed that the posterior error ratio C values of the three groups of models were 0.003–0.131, all <0.35; the small-error probability P values were all 1.000, all >0.950. According to the accuracy grading criteria of grey system theory, the modeling accuracy of all three groups reached the "excellent" grade (Table 5). The model fit test results showed that the maximum relative error of the three groups of models was 7.047%, <10.000%; except for the absolute level deviation value of 0.104 in the high-level increasing group in 2019, all level-deviation absolute values were <0.100. Taken together, these indicators show that the three GM(1,1) models had good fitting performance and predictive reliability (Table 6).

2.6 Prediction of eldercare vulnerability values among rural elderly in Xinjiang from 2026 to 2031

The relational grade test, residual test, and posterior error test indicated that the established grey prediction models achieved high accuracy and small relative errors when used to predict the eldercare vulnerability values of the three groups of rural elderly in Xinjiang from 2017 to 2025. Based on the 2017–2025 data, this model was used to predict the eldercare vulnerability values of elderly persons in different groups from 2026 to 2031; the results are shown in Figure 4.

3 Discussion

In earlier research, the research team constructed a multidimensional and quantifiable evaluation index system for eldercare vulnerability, comprising 3 dimensions at the target level, 10 first-level indicators at the criterion level, and 34 second-level indicators at the indicator level[^15]. The weight calculation results showed that four second-level indicators—living arrangement, natural disasters, widowhood, and depression—had relatively high weight coefficients and made the most prominent contributions to the composite vulnerability score. Older adults are situated at the intersection of multiple vulnerability factors; through complex mechanisms of synergistic accumulation, the above factors systematically increase the risk of impairment to older adults' physical and mental health and overall well-being. Because their children are not by their side and they lack daily companionship and life care, older adults living alone experience a marked decline in quality of life in later years. Previous studies have confirmed that living alone is positively correlated with the risk of disability, dementia, and depression[^24], and this group shows prominent characteristics of eldercare vulnerability. Existing studies have shown that older adults are susceptible to sudden natural disasters[^25]; as an exogenous shock variable, natural disasters can disrupt the integrity of family eldercare support systems, resulting in economic assistance and daily⋯

Table 3 Comparison of baseline characteristics among different vulnerability trajectory groups of older adults in rural Xinjiang

Item	Low-level stable group (n=453)	Medium-level persistent group (n=521)	High-level rising group (n=159)	$\chi^2(Z)$ value	P value
Age [n (%)]				19.846	<0.001
60–69 years	264 (58.28)	280 (53.74)	53 (33.33)		
70–79 years	141 (31.13)	224 (42.99)	101 (63.52)		

Item	Low-level stable group (n=453)	Medium-level persistent group (n=521)	High-level rising group (n=159)	$\chi^2(Z)$ value	P value
$ 80years|48(10.60),|17(3.26)|5(3.14)|||Sex[n (M, P_{25}, P_{75})$, count]				15.469^a	<0.001
Frequency of daily-life care [n (%)]				403.649	<0.001
Almost none	15 (3.31)	25 (4.8)	0		
Once every few months	15 (3.31)	96 (18.43)	2 (1.26)		
Once every 2–4 weeks	97 (21.41)	346 (66.41)	39 (24.53)		
At least once per week	137 (30.24)	38 (7.29)	55 (34.59)		
Almost every day	189 (41.72)	16 (3.07)	63 (39.62)		
Self-care ability in daily living [n (%)]				61.938	<0.001
Completely self-care	160 (35.32)	116 (22.26)	21 (13.21)		
Basically self-care	207 (45.70)	190 (36.47)	82 (51.57)		
Mild dependence	81 (17.88)	200 (38.39)	53 (33.33)		
Severe dependence	5 (1.10)	15 (2.88)	3 (1.89)		

Item	Low-level stable group (n=453)	Medium-level persistent group (n=521)	High-level rising group (n=159)	$\chi^2(Z)$ value	P value
Number of chronic diseases [n (%)]				75.162	<0.001
0 types	163 (35.98)	93 (17.85)	37 (23.27)		
1 type	180 (39.74)	208 (39.92)	56 (35.22)		
$ $2 types	110 (24.28)	220 (42.23)	66 (41.51)		
Hospitalized due to illness [n (%)]				244.233	<0.001
No	449 (99.12)	321 (61.61)	79 (49.69)		
Yes	4 (0.88)	200 (38.39)	80 (50.31)		
Main economic source for old-age support [n (%)]				67.331	<0.001
Retirement pension/old-age pension	100 (22.08)	112 (21.50)	16 (10.06)		
Subsidies from children/relatives and friends	297 (65.56)	337 (64.68)	115 (72.33)		
Government/collective subsidies	5 (1.10)	12 (2.30)	19 (11.95)		
Labor income	30 (6.62)	22 (4.22)	3 (1.89)		
Personal savings	7 (1.55)	13 (2.50)	1 (0.63)		

Item	Low-level stable group (n=453)	Medium-level persistent group (n=521)	High-level rising group (n=159)	$\chi^2(Z)$ value	P value
Housing/land rent	14 (3.09)	25 (4.80)	5 (3.14)		

Note: ^a indicates the Z value.

Table 4 Grade-ratio test of the GM(1, 1) model for different vulnerability trajectory groups

Group	Year	Original value	Grade-ratio value λ	Original value + shift-transformed shift value (shift=0)	Transformed grade-ratio value λ
Low-level stable group	2017	0.068	–	0.068	–
Low-level stable group	2019	0.071	0.956	0.068	0.956
Low-level stable group	2021	0.074	0.962	0.075	0.962
Low-level stable group	2023	0.076	0.965	0.082	0.965
Low-level stable group	2025	0.093	0.818	0.090	0.818
Medium-level persistent group	2017	0.126	–	0.126	–

Group	Year	Original value	Grade-ratio value λ	Original value + shift-transformed shift value (shift=0)	Transformed grade-ratio value λ
Medium-level persistent group	2019	0.137	0.920	0.134	0.920
Medium-level persistent group	2021	0.143	0.958	0.146	0.958
Medium-level persistent group	2023	0.158	0.906	0.158	0.906
Medium-level persistent group	2025	0.173	0.911	0.172	0.911
High-level rising group	2017	0.239	–	0.239	–
High-level rising group	2019	0.291	0.823	0.288	0.823
High-level rising group	2021	0.312	0.932	0.313	0.932
High-level rising group	2023	0.338	0.924	0.341	0.924

Group	Year	Original value	Grade-ratio value λ	Original value + shift-transformed shift value (shift=0)	Transformed grade-ratio value λ
High-level rising group	2025	0.375	0.900	0.372	0.900

Note: —indicates no corresponding data.

Table 5 Parameter estimation and accuracy test results of the GM(1, 1) model for different vulnerability trajectory groups

Group	Development coefficient	Gray action quantity	Posterior variance ratio C value	Small error probability P value
Low-level stable group	−0.092	0.059	0.131	1.000
Medium-level persistent group	−0.082	0.119	0.012	1.000
High-level rising group	−0.085	0.255	0.003	1.000

Table 6 Goodness-of-fit test (residual test) results of the GM(1, 1) model for different vulnerability trajectory groups

Group	Year	Original value	Predicted value	Residual	Relative error	Grade-ratio deviation
Low-level stable group	2017	0.068	0.068	0.000	0.000%	–

Group	Year	Original value	Predicted value	Residual	Relative error	Grade-ratio deviation
Low-level stable group	2019	0.071	0.068	0.003	4.127%	−0.048
Low-level stable group	2021	0.074	0.075	−0.001	1.148%	−0.055
Low-level stable group	2023	0.076	0.082	−0.005	7.047%	−0.058
Low-level stable group	2025	0.093	0.090	0.004	3.962%	0.103
Medium-level persistent group	2017	0.126	0.126	0.000	0.000%	–
Medium-level persistent group	2019	0.137	0.134	0.003	1.834%	0.002
Medium-level persistent group	2021	0.143	0.146	−0.003	2.024%	−0.039
Medium-level persistent group	2023	0.158	0.158	−0.001	0.350%	−0.016
Medium-level persistent group	2025	0.173	0.172	0.001	0.802%	0.011

Group	Year	Original value	Predicted value	Residual	Relative error	Grade-ratio deviation
High-level rising group	2017	0.239	0.239	0.000	0.000%	–
High-level rising group	2019	0.291	0.288	0.003	1.018%	0.104
High-level rising group	2021	0.312	0.313	−0.001	0.449%	−0.015
High-level rising group	2023	0.338	0.341	−0.004	1.110%	−0.007
High-level rising group	2025	0.375	0.372	0.003	0.861%	0.019

Note: –indicates no corresponding data.

Figure 4. Trajectory and predicted trend of the family-based eldercare vulnerability index among older adults in rural Xinjiang from 2017 to 2031

Y-axis: family-based eldercare vulnerability index. X-axis: year. Legend: low-level stable group (V1)—actual vulnerability index; medium-level sustained group (V2)—actual vulnerability index; high-level rising group (V2)—actual vulnerability index; low-level stable group (V1)—predicted vulnerability index; medium-level sustained group (V2)—predicted vulnerability index; high-level rising group (V2) —predicted vulnerability index. Annotated values: for 2017, 2019, 2021, 2023, 2025, 2027, 2029, and 2031, the low-level stable group is 0.068, 0.071, 0.074, 0.076, 0.093, 0.098, 0.108, and 0.118; the medium-level sustained group is 0.126, 0.137, 0.143, 0.158, 0.173, 0.186, 0.202, and 0.219; and the high-level rising group is 0.239, 0.291, 0.312, 0.338, 0.375, 0.405, 0.441, and 0.48.

care, emotional support, and other eldercare resources, thereby further aggravating the degree of eldercare vulnerability. A spouse is the core support for family-based eldercare; widowhood not only causes severe psychological trauma but is also closely associated with deterioration in physical health

. Constrained by traditional ideas and the social environment, older adults have a relatively low willingness to remarry, which further compresses potential sources of family caregiving[27]. Depression in later life has become an important public health problem impeding healthy aging; its negative effects extend beyond psychological distress and impose a relatively heavy economic burden and eldercare pressure on individuals, families, and society[28].

The results of this study show that from 2017 to 2025, the overall family-based eldercare vulnerability of older adults in rural Xinjiang showed a slowly rising trend. Clustering with the GBTM model divided the developmental trajectories into three types: a low-level stable type, a medium-level sustained type, and a high-level rising type, indicating marked population heterogeneity in the evolution of eldercare vulnerability. Among them, the medium- and high-level trajectory populations together accounted for 58.1%, which is close to the proportion of moderately and highly vulnerable groups found in Xu Jie' s cross-sectional study of rural Anhui[28]. In addition, existing literature has pointed out that the overall level of eldercare vulnerability in western China is higher than the national average[29], corroborating that the eldercare pressure faced by older adults in rural Xinjiang is relatively heavy and urgently requires supportive policy tilting.

The trajectory analysis shows that the vulnerability index of the low-level stable group remains low year-round, with relatively small temporal fluctuations. This group has relatively complete existing family-based eldercare functions and can withstand routine eldercare risks; however, without advance intervention, there is a latent risk that vulnerability will rise, making them "implicitly vulnerable families." The vulnerability index of the medium-level sustained group rose slightly from 2023 to 2025, with a modest increase; nevertheless, family-based eldercare risks continued to accumulate, and this group is gradually entering a high-incidence zone of eldercare difficulties. The high-level rising group showed the most pronounced increase in the vulnerability index. Under the influence of multiple social-environmental factors, including accelerated population aging, family miniaturization, weakened intergenerational care, and interregional population mobility, the contradiction between eldercare and health security in this group is prominent. Further analysis indicates that such families have insufficient reserves of family-based eldercare resources, such as economic income and caregiving resources, making it difficult for them to offset internal and external risks. After the outbreak of the coronavirus disease 2019 pandemic in 2020, the vulnerability index of this group fluctuated sharply, confirming that its family-based eldercare support system is weak in resilience and highly susceptible to shocks from external emergencies.

Overall, family-based eldercare vulnerability among older adults in rural Xinjiang lies in the medium-to-high range, and the indicators for the moderately and highly vulnerable groups have increased year by year, suggesting that the pressure on local rural families to provide eldercare will continue to intensify. The underlying reasons are that the regional eldercare security system has limited capacity to bear pressure, accelerated population aging continues to force improvements in the social security system, and livelihood issues related to eldercare and medical care have become increasingly prominent. Accurately anticipating trends in eldercare vulnerability can help deploy preventive and control measures in advance. Among existing prediction models, machine-learning algorithms depend on large-sample data; under small-sample conditions, overfitting is likely to occur, and the black-box nature of the models leads to insufficient interpretability of results. Existing systematic reviews have confirmed that sample scarcity and overfitting are common shortcomings of prediction models for frailty in older adults[30]. By comparison, the grey prediction model GM(1,1) requires only no fewer than four groups of time-series data to build a model, imposes no rigid constraints on data distribution, and is suitable for small-sample research scenarios. The model has only two parameters, a and b, is easy to compute, and produces highly readable results, facilitating implementation in decision-making. Existing empirical studies have verified its applicability: Shanghai used 10 years of time-series data and adopted GM(1,1) to achieve precise prediction of regional institutional eldercare supply[31]; Nantong University used this model to complete projections of aging trends in Jiangsu Province, with good predictive performance[32]. Meanwhile, grey models have obvious advantages in regions with incomplete data. Gansu Province carried out agricultural carbon-emission estimation based on short time-series data, and GM(1,1) still maintained relatively high prediction accuracy[33]. In summary,

GM(1,1) is suitable for short-term trend forecasting of old-age care vulnerability among rural older adults in Xinjiang. However, constrained by random disturbances such as policy changes and economic fluctuations, as well as by system complexity, the model' s long-term forecasting accuracy gradually declines[^34].

Therefore, this study estimates vulnerability only for the next 6 years (3 forecasting cycles). Validation shows that the model has a good fitting effect and conforms to the historical pattern of evolution; the forecasting conclusions have reference value and can subsequently be extended to research related to old-age care vulnerability.

The baseline characteristics of the high-level rising group are mainly advanced age, severe disability, and high dependence on public assistance. The forecast results show that the old-age care vulnerability index of this group will continue to rise, reflecting insufficient family-owned old-age care resources to offset risks, and that the old-age care predicament has become an established trend and continues to worsen. Emergency intervention plans should be proposed for this population: relying on administrative villages to establish dynamic monitoring ledgers for highly vulnerable older adults; conducting quarterly investigations of the physical and mental health and living conditions of older adults living alone, widowed older adults, and older adults in disaster-prone areas; equipping the target population with one-touch emergency-call smart bracelets and connecting them to 120 emergency services and village-level grid workers to achieve emergency door-to-door assistance within 15 min; increasing the weighting of basic pension funds toward older adults living alone and at advanced ages, and giving priority to including highly vulnerable groups in the civil affairs department's regular visiting and assistance list for older adults with special difficulties; government procurement of respite care and daytime custody services from eldercare institutions to reduce the burden on in-home caregivers; and provision of free psychological counseling services for widowed older adults.

The medium-level sustained group is characterized mostly by mild-to-moderate disability, a relatively high proportion of widowed individuals, and absent care from children. The vulnerability index will rise slowly, with risks continuing to accumulate and latent old-age care disability risks. Preventive interventions should be implemented: compiling a simple screening scale for old-age care vulnerability, with village doctors incorporating it into routine household assessments; including widowed older adults within the scope of special care subsidies, with subsidy funds used for home nursing and meal-assistance services; relying on the rural custom of neighborhood mutual aid and forming neighborhood mutual-aid care groups in units of 3–5 households; providing targeted training for caregivers in families at high warning risk, popularizing knowledge on chronic disease management and emergency rescue; housing and construction departments providing earthquake-resistant renovation subsidies for older adults living in dilapidated housing; organizing at least one disaster-prevention drill each year at the village level to reduce the impact of natural disasters on home-based eldercare; upgrading cultural and entertainment services at village-level senior activity centers to enrich older adults' spiritual life; and relying on policy guidance and filial-piety publicity to strengthen children' s awareness of support and restore the family caregiving function.

The low-level stable group still has a foundation of physical and mental health and family caregiving, but empty-nest families account for a relatively high proportion, and hidden depression risks persist over the long term. Forecasts show that the vulnerability index of this group is generally stable and that the buffering mechanism of existing family eldercare remains effective; however, with increasing age, various frailty-inducing factors gradually accumulate, and advance prevention and control are still needed. Corresponding consolidation interventions include: implementing supporting smart eldercare facilities in rural areas; providing moderate subsidies to families of migrant workers for installing smart door sensors, fall-detection devices, and heart-rate monitoring bracelets, with monitoring data synchronized to the township health-center early-warning platform; guiding age-appropriate families to take out long-term care insurance to disperse the risk of large family expenditures on eldercare; promoting time-bank mutual-aid eldercare, pairing younger healthy older adults with older adults living alone at a 1:1 ratio to provide no fewer than 4 h of monthly home companionship or proxy services, with service time converted into eldercare points for later exchange for care.

4 Conclusion

Over the next three years, the vulnerability of family-based eldercare among rural older adults in Xinjiang will continue to remain at a medium-to-high level, and the degree of vulnerability will continue to deepen. Therefore, relevant departments urgently need to formulate precise eldercare response strategies. By establishing an intelligent monitoring platform for old-age care vulnerability[^35], implementing differentiated eldercare subsidy policies[^36], and cultivating rural eldercare-service social organizations, the level of old-age care vulnerability among rural older adults can be effectively reduced. At the same time, the traditional family eldercare culture of filial piety and respect for the elderly should be vigorously promoted throughout society, consolidating the principal role of family eldercare in rural areas and helping to build a new rural eldercare pattern in which "older adults have support, care, and joy."

Author contributions: You Shuping proposed the main research objectives; Meng Na was responsible for the research conception, study design, project implementation, data collection, manuscript writing, and statistical analysis; Aifire·Abeibao participated in data collection and figure/table preparation; Wu Pei, Liu Qin, and Huang Mengsi assisted with data collection; You Shuping was responsible for manuscript revision, quality control, and overall review, and takes responsibility for the article as a whole.

The authors declare no conflicts of interest.

Meng Na ORCID: https://orcid.org/0009-0002-2679-9677

References

[1] Wang Z S, Chen X F, Ji K, et al. Relationship between social network

and individual performance of core members from aged care services social organizations: cross-sectional study[J]. BMC Geriatr, 2023, 23(1): 108. DOI: 10.1186/s12877-023-03837-x.

[2] Zhang P R, Liu Y W. The higher the children' s achievements, the better the elderly health? evidence from China[J]. Front Public Heal, 2022, 10: 871266. DOI: 10.3389/fpubh.2022.871266.

[3] Zhou W J, Hou J M, Sun M, et al. The impact of family socioeconomic status on elderly health in China: based on the frailty index[J]. Int J Environ Res Public Heal, 2022, 19(2): 968. DOI: 10.3390/ijerph19020968.

[4] Naaman R K. Nutrition behavior and physical activity of middle-aged and older adults in Saudi Arabia[J]. Nutrients, 2022, 14(19): 3994. DOI: 10.3390/nu14193994.

[5] Yu Changyong, He Jian. Concept, analytical framework, and analysis of frailty in peasant eldercare[J]. Rural Economy, 2011(8): 88–91. DOI: 10.26957/j.cnki.cn51-1029/f.2011.08.021.

[6] Zhou Jianfang. The evolutionary mechanisms and forward-looking governance of health and safety risks from rural population aging during the "15th Five-Year Plan" period[J]. Modern Economic Research, 2026(5): 122–132. DOI: 10.13891/j.cnki.mer.2026.05.010.

[7] Li Chunling, Chen Hongyun, Li Haomiao. Study on trends and risk factors of frailty among middle-aged and older adults in rural China[J]. Soft Science of Health, 2022, 36(1): 20–25. DOI: 10.3969/j.issn.1003-2800.2022.01.006.

[8] Wang Ping, Li Xian, Pan Shuang. "Distance" and "harmony" cannot both be achieved: intergenerational relationships in rural older-adult families from the perspective of distance and their mechanisms[J]. Population & Economics, 2025(1): 61–77.

[9] Zhao Liqin, Cui Yue. Measurement of old-age care vulnerability among China' s elderly population and analysis of influencing factors: based on CLHLS2014 data[J]. Survey World, 2019(3): 32–36. DOI: 10.13778/j.cnki.11-3705/c.2019.03.007.

[10] Ma Yang, Sun Zekun, Li Zeyu, et al. Evaluation of eldercare vulnerability in rural families based on risk exposure, sensitivity, and coping capacity[J]. Chinese Journal of Health Statistics, 2023, 30(4): 263–268, 274. DOI: 10.3969/j.issn.1006-5253.2023.04.005.

[11] Gan Xiaocheng, Cai Yaoyao, Xiao Hongbo. Evaluation and distributional dynamic evolution of old-age care vulnerability in China[J]. East China Economic Management, 2022, 36(2): 86–97. DOI: 10.19629/

j.cnki.34-1014/f.210922001.

[12] Wang Bin. Current health status, changing trends, and socioeconomic impacts of China' s older population: an analysis based on data from the "Seventh

National Population Census" [J]. Journal of Yunnan Minzu University (Philosophy and Social Sciences Edition), 2022, 39(5): 68–75. DOI: 10.13727/j.cnki.53-1191/c.20220905.007.

[13] Chen Xinxin, Chen Yanfeng, Gong Jinquan, et al. Challenges facing eldercare for rural older adults in China and prominent problems in eldercare services[J]. Journal of China Agricultural University (Social Sciences Edition), 2021, 38(4): 64–77. DOI: 10.13240/j.cnki.caujsse.2021.04.005.

[14] Xiong Wei, Yu Changyong. Study on the impact of old-age support resources on farmers' eldercare risks: an empirical analysis based on survey data from 726 farmers in 13 prefectures and cities in Xinjiang[J]. Journal of Southwest Minzu University (Humanities and Social Sciences Edition), 2019, 40(12): 31–39.

[15] Meng Na, You Shuping, Liu Tao, et al. Vulnerability assessment and barrier-factor analysis of family eldercare among elderly farmers and herders in the pastoral areas of southern Xinjiang[J]. Modern Preventive Medicine, 2024, 51(6): 1044–1049. DOI: 10.20043/j.cnki.MPM.202309329.

[16] Nagin D S, Jones B L, Elmer J. Recent advances in group-based trajectory modeling for clinical research[J]. Annu Rev Clin Psychol, 2024, 20(1): 285–305. DOI: 10.1146/annurev-clinpsy-081122-012416.

[17] Xu Zedong, Liu Fuxiang. A review of research progress on optimization of the grey GM(1,1) model[J]. Computer Science, 2016, 43(S2): 6–10.

[18] Fan Jingling, Zhang Xuelian, Yang Fei, et al. Analysis of eldercare service needs and influencing factors among 1,652 rural older adults[J]. Journal of Xinjiang Medical University, 2021, 44(3): 377–382. DOI: 10.3639/j.issn.1009-5551.2021.03.023.

[19] Liang Xia. Multiple imputation of missing data and its improvement[D]. Changsha: Central South University, 2007.

[20] Wei Z Q, Ji D D, Yang L. Comprehensive evaluation of water resources carrying capacity in Henan Province based on entropy weight TOPSIS -coupling coordination -obstacle model[J]. Environ Sci Pollut Res Int, 2023, 30(54): 115820–115838. DOI: 10.1007/s11356-023-30456-1.

[21] Nagin D S. Group-based trajectory modeling[J]. Ann Nutr Metab, 2014, 65(2/3): 205–210.

[22] Xu Zedong, Liu Fuxiang. A review of research progress on optimization of the grey GM(1,1) model[J]. Computer Science, 2016, 43(S2): 6–10.

[23] Peng F, Peng L, Huang X. GM(1, 1) modeling principle analysis[J]. J Grey Syst, 2013, 25(1): 87–95.

[24] Chen Y. Risk factors for depression among older adults living alone in Shanghai, China[J]. Psychogeriatrics, 2022, 22(6): 780–785. DOI: 10.1111/psyg.12882.

[25] Evans J. Mapping the vulnerability of older persons to disasters[J]. Int J Older People Nurs, 2010, 5(1): 63–70. DOI: 10.1111/j.1748-3743.2009.00205.x.

[26] Coundouris S P, Hohn S, Basu A, et al. Cognition and financial decision-making in older adult spouses[J]. Gerontology, 2023, 69(9): 1128–1136. DOI: 10.1159/000531193.

[27] Kim J Y, Xu H Z, Cruz G, et al. Acceptance of love and remarriage among older adults in the Philippines[J]. J Aging Health, 2021, 33(5/6): 331–339. DOI: 10.1177/0898264320981246.

[28] Xu Jie, Li Shuzhuo, Wu Zheng, et al. Vulnerability assessment of family eldercare for rural older adults: an empirical study based on rural areas in Anhui[J]. Population Research, 2019, 43(1): 91–101.

[29] Li Wenyan. Analysis of eldercare vulnerability and risk early warning in rural areas of China[D]. Taiyuan: Shanxi University of Finance and Economics, 2023.

[30] Cheng Juning, Liu Jinxu, Zhuang Yiyu, et al. Systematic evaluation of a prediction model for frailty risk among community-dwelling older adults[J]. Chinese Journal of Modern Doctor, 2023, 61(6): 73–78. DOI: 10.3969/j.issn.1673-9701.2023.06.019.

[31] Xiao Li. Prediction and analysis of the supply of institutional eldercare services in Shanghai based on the GM(1, 1) grey prediction model[J]. Advances in Applied Mathematics, 2022, 11(9): 6255–6264. DOI: 10.12677/AAM.2022.119661.

[32] Guo X J, Wu Y, Wang Y Y, et al. 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[J]. BMC Geriatr, 2025, 25(1): 197. DOI: 10.1186/s12877-025-05848-2.

[33] He Libo, Ren Suling. Prediction and analysis of agricultural carbon emissions in Gansu Province based on grey prediction and decoupling models[J]. Journal of Northern Agriculture, 2024, 52(2): 87–96. DOI: 10.12190/j.issn.2096-1197.2024.02.10.

[34] Lan J Y, Zhou Y. Application of gray Markov SCGM(1, 1)c model to prediction of accidents deaths in coal mining[J]. Int Sch Res Notices, 2014, 2014: 632804. DOI: 10.1155/2014/632804.

[35] Chen Xin, Lu Yihua. The value mechanism, practical bottlenecks, and mechanism innovation of digital-intelligence empowerment for the high-quality development of urban eldercare services[J]. Nanjing Journal of Social Sciences, 2025(2): 65–74. DOI: 10.15937/j.cnki.issn1001-8263.2025.02.007.

[36] Zhang Ning, Li Minqi. Can government subsidies increase farmers' willingness to pay pension insurance premiums? A simulation analysis based on an

incremental discounted utility model[J]. Economic Science, 2020(3): 123–136. DOI: 10.12088/PKU.jjkx.2020.03.10.

(Received: 2025-11-14; revised: 2026-04-29)

(Editor: Wang Fengwei)

Note: Figure translations are in progress. See original paper for figures.