Article

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Development Analyses and Strategies for Pet Industry and related Industries

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Abstract: With the rapid economic development and people's pursuit of spiritual life, the pet industry has gradually risen around the world. Taking the pet industry and its related derivative industries as the research object, this paper uses various mathematical modeling methods to conduct in-depth research on the development of the pet industry in China and around the world, so as to analyze the development of the pet industry in China and even around the world, predict the change of pet food output and the development of the pet food industry, and provide some ideas for the sustainable development of the pet food industry in China.

Keywords: regularization regression; ARIMA; PLSR; pet industry development

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1. Introduction

1.1. Background Check

With the continuous development of people's consumption concept and the growth of per capita income, in recent years, the pet industry has gradually formed a momentum of development in the world. At the same time, with the growing popularity of "pet companions" in China, pet-related industries have gradually enjoyed a broad and rapidly growing market. Therefore, analyzing and forecasting the development trend and market demand of the pet industry has become a key issue that needs to be solved.

Annexes 1 to 3 show the number of pet cats and dogs in China, the number of pet cats and dogs abroad, and the production and export value of pet food in China from 2019 to 2023, respectively.

Due to the small number of data samples given, we need to collect more comprehensive and complete data to complete the development analysis of pets and related industries.

1.2. Problem Analysis

Question 1

First of all, we are required to analyze the development of the pet industry in the past five years according to the types of pets. At the same time, since the development of the pet industry is affected by many factors, we are required to find out and analyze these influencing factors and establish a model to predict the development of China's pet industry in the next three years. Based on the number of pets, we analyze the development of China's pet industry in the past five years using a grey prediction model. By using partial least squares regression and ARIMA model based on principal component analysis [1], we analyze the development factors of pet industry and predict its development in the next three years.

Question 2

We were asked to analyze the development of the global pet industry by pet type and build a model to forecast the global demand for pet food in the next three years.

Question 3

Question 3 focuses on China's pet food industry. It requires us to analyze the development of China's pet food industry and forecast the production and export of pet food in China in the next three years according to the food production and export situation in the attachment.

Question 4

China's pet food industry is affected by foreign economic policies. Therefore, this paper hopes to combine the results of the first three questions and the collected data to establish a suitable mathematical model to quantitatively analyze this impact and formulate feasible strategies for the sustainable development of China's pet food industry [2].

2. Hypothesis and Symbol Description

2.1. Hypothesis

1) Assume that the rate of pet food production and the cost of production have not changed significantly over the past few years.
2) It is assumed that the influence of historical data on future observations continues to expand over time.
3) It is assumed that the data source is accurate and reliable, and all data are true records.
4) Suppose that the changes in the number of pets in question 1 can roughly represent the development trend of the pet industry; The output and export volume of China's pet food can better represent the development of China's pet food industry.

2.2. Symbol Specification

Some of the symbols used in this article are presented in Table 1

Table 1. Symbol specification.

Symbol	Description
$X(0)$	Raw data matrix
$\lambda(k)$	Grade ratio
$\varepsilon(k)$	Relative residuals
S_i	standard deviation
$E0$ $F0$	Normalization matrix
$Cov(,)$	covariance
β	Regression coefficients
λ output	Penalty factor

3. Question 1: Influencing Factors and Prediction of the Development of China's Pet Industry

3.1. Analysis of the Development of China's Pet Industry in the Past Five Years

Since most families have cats and dogs as pets, we collected the relevant data of China's pet industry from 2019 to 2023 and used the gray prediction model to fit and forecast the pet industry according to the pet types, so as to analyze the development of China's pet industry in the past five years [3]. In addition, we used a linear regression model for dogs and a quadratic exponential smoothing model for cats respectively to fit the above data and compare it with the gray prediction model to check the accuracy of our model.

3.1.1. Model Building and Visualization

Grey prediction model

Since the population growth of cats and dogs is relatively complicated, we choose to use the gray prediction model, because the gray prediction model can predict the future population change more accurately by using the small sample number information based on the existing data [4,5].

1) Data level ratio test

If a set of data can be predicted by grey model, it is necessary to conduct data test on the level ratio of the original sequence to check whether the level ratio falls in the level ratio interval. Raw data column $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, The level ratio of the sequence is calculated using the following formula (1).

$$\lambda(k) = \frac{x^{(0)}(k-1)}{x^{(0)}(k)}, k = 1, 2, 3, \ldots, n \quad (1)$$

If all the stage ratios are calculated $\lambda(k)$ fall interval $(\frac{e-2}{(n+1)}, \frac{e-2}{(n+2)})$, n according to the data sample of the specific sequence, the sequence can be gray forecast.

From the analysis of Table 2 and Table 3, it can be seen that all pole ratios of the cat and dog original sequences are within the interval (0.717, 1.396), indicating that the cat and dog original sequences are suitable for building gray prediction models.

Table 2. Grading test results table for cats.

index entry	Raw value	Grade ratio
2019	4412	
2020	4862	0.907
2021	5806	0.837
2022	6536	0.888
2023	6980	0.936

Table 3. Grading test results table for dogs.

index entry	Raw value	Grade ratio
2019	5503	
2020	5222	1.054
2021	5429	0.962
2022	5119	1.061
2023	5175	0.989

2) GM (1,1) model construction

Based on the original data column $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}$, Let

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

Add the data column once to generate a new sequence, i.e.

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\}\ n$$

is the number of data samples to obtain the mean sequence

$$z^{(1)}(k) = \frac{1}{2}\{x^{(1)}(k) + x^{(1)}(k-1)\}, k = 2, 3, \ldots, n$$

Construct grey differential equation:

$$x^{(0)}(k) + az^{(1)}(k) = b \quad (2)$$

By solving equation (2), the development coefficient and grey action b are obtained. The corresponding differential equation of GM (1,1) whitening is as follows:

$$\frac{dx^{(1)}}{dt} + ax^{(1)}(t) = b \quad (3)$$

The discrete solution of GM (1,1) model is obtained as follow

$$\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-\alpha(k-1)} + \frac{b}{a} \quad (4)$$

The original sequence model is obtained:

$$\hat{x}^{(0)}(k) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-\alpha(k-1)} + (1 - e^{a}) \quad (5)$$

3) Accuracy check

Calculate relative residuals ε(k):

$$\varepsilon(k) = \left|\frac{x^{(0)}(k) - \widehat{x^{(0)}(k)}}{x^{(0)}(k)}\right| \quad (6)$$

If $\varepsilon(k) < 0.1$,it is believed that the accuracy of the predicted results is high. If $\varepsilon(k) < 0.1$, it is believed that the accuracy of the predicted results is average.

Posterior difference ratio test C value:

$$C = \frac{S_2}{S_1} \quad (7)$$

Among,

$$S_1 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}[x^{(0)}(k) - \bar{x}]^2} \;,\; S_2 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}[\varepsilon(k) - \bar{\varepsilon}]^2}$$

Small error probability P:

$$P = \{|\varepsilon - \bar{\varepsilon_1}| < 0.6745 S_1\}$$

The following table shows the development coefficient, grey action, and posterior difference ratio. The grey prediction model can be constructed from the development coefficient and grey action.

The development coefficient represents the development law and trend of the series, and the grey action reflects the change relationship of the series.

The posterior difference ratio can verify the accuracy of grey prediction, and the smaller the posterior difference ratio, the higher the accuracy of grey prediction.

Generally, if the C value of the posterior difference ratio is less than 0.35, the model accuracy is high; if the C value is less than 0.5, the model accuracy is qualified; if the C value is less than 0.65, the model accuracy is basically qualified; if the C value is greater than 0.65, the model accuracy is unqualified.

According to the analysis of Table 4 and Table 5, the posterior difference ratio of cat is 0.023, indicating a high precision of the model. The posterior difference ratio of dogs is 0.4, and the accuracy of the model is qualified.

Table 4. Grey prediction model construction for cats.

Development coefficient a	Gray effect b	Posterior difference ratio C
-0.115	4250.83	0.023

Table 5. Grey prediction model construction for dogs.

Development coefficienta a	Gray effect b	Posterior difference ratio C
0.009	5373.532	0.4

4) Model prediction result

The following table shows the fitting result table of the grey prediction model. The smaller the relative error value, the better. Generally, less than 20% means that the fit is good.

According to the analysis in Table 6 and Table 7, the average relative error of cat model fitting is 2.236% and that of dog model fitting is 1.333%, both of which mean that the model fitting effect is good.

Table 6. Model fitting results table for cats.

Forecast year	Predicted value
2024	7985.195
2025	8957.829
2026	10048.934
Forecast year	Predicted value
2024	7985.195
2025	8957.829
2026	10,048.934
2026	10,048.934

Table 7. Model fitting results table for dogs.

index entry	Raw value	Predicted value	Residuals	relative error(%)
2019	5503	5503	0	0
2020	5222	5303.669	-81.669	1.564
2021	5429	5258.447	170.553	3.142
2022	5119	5213.611	-94.611	1.848
2023	5175	5169.157	5.843	0.113

The Table 8 and Table 9 is the prediction results table of the grey prediction model and the fitting prediction graph Figure 1 and Figure 2 are shown below.

Table 8. fitting results table for cats.

index entry	Raw value	Predicted value	Residuals	relative error(%)
2019	4412	4412	0	0
2020	4862	5042.16	-180.16	3.705
2021	5806	5656.318	149.682	2.578
2022	6536	6345.284	190.716	2.918
2023	6980	7118.169	-138.169	1.979

Table 9. fitting results table for dogs.

Forecast year	Predicted value
2024	5125.083
2025	5081.384
2026	5038.057

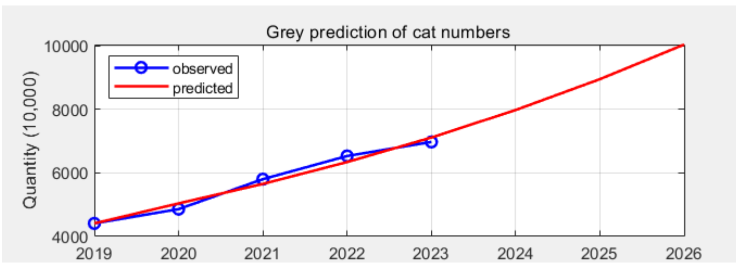


Figure 1. The gray prediction model fits the prediction map of cats.

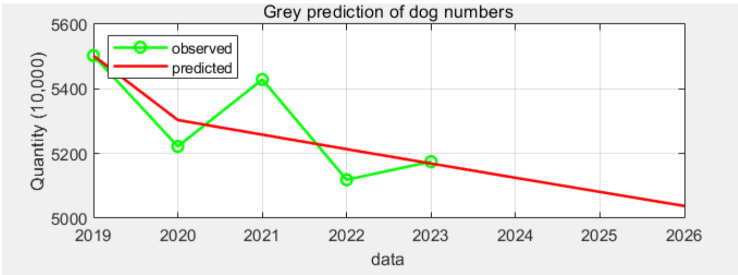


Figure 2. The gray prediction model fits the prediction map of dogs.

3.1.2. Quadratic Exponential Smoothing Method and Linear Regression were used to Verify the Prediction Results of Cats and Dogs

Figure 3 and Figure 4 shows that this prediction is similar to the gray prediction. Therefore, it can be judged that the prediction results of the grey prediction model are reliable.

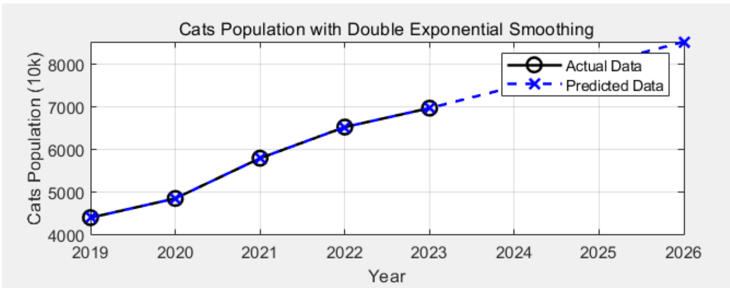


Figure 3. Quadratic exponential smooth-fitting prediction plot for cats.

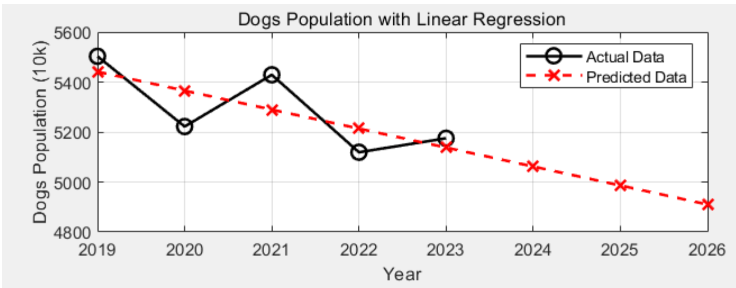


Figure 4. Quadratic exponential smooth-fitting prediction plot for dogs.

3.1.3. Result Analysis

From the above gray prediction model, from the analysis and prediction of the development of cats and dogs in the past five years, since 2019, the pet industry has continued to upgrade, the concept of scientific pet raising and healthy pet raising has gradually become popular, the status of pets in the minds of pet owners has continued to rise, and the pet lifestyle such as exquisite pet raising and intelligent pet raising has prompted the explosive growth of the diversified market segments of the pet industry. Pet dogs and cats are still the most popular pet groups, and a wider proportion of pet types are raised. In comparison, the number of urban dog feeding in 2022 fell slightly, and the number and proportion of pet cats with less need to go out were still expanding due to the impact of the three-year home situation of the epidemic. However, with the recovery of the offline economy the demand for going out will pick up, and the scale of pet dog feeding and economic development will also usher in a new round of growth.

3.2. Modeling and Analysis of Related Development Factors

We collected data on indicators such as the number of pets, pet food production, household penetration, and market size (Figure 5). Since these indicators have strong time regularity, we mainly fore- cast the development of China's pet industry based on the ARIMA model. In addition, in order to better show the relationship between these indicators and make predictions for multiple indica- tors at the same time, we use the partial least squares regression model to deal with the problem of multiple correlations. In addition, we further improve our model from the aspects of human-pet relationship, consumption awareness, economic growth, population structure and China's poverty alleviation policies.

Figure 5. Factors influencing the development of China's pet industry.

3.2.1. Model Building

Partial least squares regression model

Partial least squares regression combines principal component analysis and linear regression. This characteristic makes it different from other methods in data processing, it can effectively deal with multiple correlation problems, and pay more attention to the interpretation of independent variables and dependent variable parameters.

Partial least squares regression modeling based on multivariate variables needs to standardize the corresponding n × p-order independent variable matrix X and n × q-order dependent variable matrix Y to obtain the corresponding standardized matrices E_0 and F_0 .

After processing the matrix, you can do the following:

$$x_{ij}^{*} = \frac{x_{ij} - x_j}{S_j}$$

Among i = 1, 2, ..., n; j = 1, 2, ..., p;

$$y_{ik}^{*} = \frac{y_{ik} - y_k}{S_k}$$

Among i = 1, 2, ..., n; k = 1, 2, ..., 1; and the final formula is:

$$E_0 = {x_{ij}^{*}}_{n\times p} \ , \ F_0 = {y_{ik}^{*}}_{n\times q}$$

Interpret the function corresponding to the coefficients in the above formula as $x_{\bar{j}}$ is the average of x_j,And the corresponding S_j is the standard deviation of x_j; Similarly, for y, $y_{\bar{k}}$ is the mean of y_k , and the corresponding S_k is the standard deviation of y_k.

After obtaining the corresponding standardized matrix, it is necessary to extract the corresponding components according to the same idea. Firstly, the first component is extracted from x_0 and denoted as $t_1 = E_0\, w_1$; similarly, the first component in the standardized dependent variable matrix is denoted as $\mu_1 = F_0\, c_1$, and the two components t_1 and u_1 obtained must meet the data variation information that can well represent the independent variable matrix X and dependent variable matrix Y, respectively. The so-called variation information of the data is actually to compare all the elements in the array with a specific value, usually the mean value of the entire array, and the indicators that reflect the variation information of the data are usually compared with range, standard deviation and variance. According to the principle of principal component analysis, the corresponding component should meet the following conditions before it can be regarded as a qualified component:

$$var(t_1) \rightarrow max$$
$$var(u_1) \rightarrow max$$

Where var () represents the variance of the corresponding component.

On the other hand, according to the correlation analysis idea of typical correlation, since these components need to be used for modeling, t_1 and u_1 need to have great explanatory ability for the whole model, so the correlation between the two components should reach the maximum value, which can be expressed by the formula:

$$r(t_1, u_1) \rightarrow max$$

To sum up, in the process of modeling partial least squares regression of multivariate variables, we need to consider maximizing the covariance of the two components t_1 and u_1 obtained, that is to say:

$$cov(t_1, u_1) = \sqrt{var(t_1)var(u_1)}\, r(t_1, u_1) \rightarrow max$$

The whole process mentioned above should be expressed in a mathematical expression to solve the optimization problem in the following formula:

$$max\ \left\langle E_0\, w_1, F_0\, c_1 \right\rangle$$
$$s.t \begin{cases} \|w_1\|^2 = 1 \\ \|c_1\|^2 = 1 \end{cases}$$

The Lagrange algorithm can be used for calculation, denoted by $\theta_1 = w_1' E_0' F_0 a_1$, that is, the value of the desired objective function is obtained according to the Lagrange method to obtain the first axis w_1 , c_1 , which can be obtained:

$$E_0' F_0 a_1 = \theta_1 w_1$$
$$F_0' E_0 w_1 = \theta_1 c_1$$

The combination of the two formulas can be obtained:

$$E_0' F_0\ F_0' E_0 w_1 = \theta_1^2 w_1$$

And by the same token, we get the formula for c_1. Find w_1 , c_1 , where w_1 corresponds to the unit eigenvector of the largest eigenvalue θ_1^2 of the matrix $E_0' F_0\ F_0' E_0$. On the other hand, c_1 is the unit eigenvector corresponding to the largest eigenvalue θ_1^2 of$F_0' E_0\ E_0' F_0$. Therefore, after solving w_1 , c_1 , the final composition is:

$$\begin{cases} t_1 = E_0 w_1 \\ t_2 = F_0 c_1 \end{cases}$$

According to this formula, the regression equation corresponding to E_0 and F_0 on t_1 can be obtained, which can be expressed as:

$$E_0 = t_1 p_1' + E_1 F_0 = t_1 r_1' + F_1$$

Among them, in the above formula: p_1 and r_1 are regression coefficients, which can be expressed as:

$$p_1 = \frac{E_0' t_1}{\|t_1\|^2}$$
$$r_1 = \frac{F_0' t_1}{\|t_1\|^2}$$

The corresponding final residual matrix can be obtained as:

$$E_1 = E_0 - t_1' p_1$$

$$F_1 = F_0 - t_1'r_1$$

After obtaining the corresponding residual matrix, replace the original standardized matrix E_0 and F_0 with the obtained residual matrix, and then repeat the process of the previous step, the corresponding new regression equation can be obtained as follows:

$$E_1 = t_2'p_2 + E_2$$
$$F_1 = t_2'r_2 + F_2$$

Similarly, parameters p_2 and r_2 in the above equation are the corresponding regression coefficients, which can be expressed as:

$$p_2 = \frac{E_1't_2}{\|t_2\|^2}$$
$$r_2 = \frac{F_1't_2}{\|t_2\|^2}$$

Iterating in this form, assuming that the rank of the original argument matrix is a, the resulting linear expression is:

$$\begin{cases} E_0 = t_1p_1' + t_2p_2' + \cdots + t_ap_a' \\ F_0 = t_1r_1' + t_2r_2' + \cdots + t_ar_a' + F_a \end{cases}$$

According to the modeling process of single dependent variables, it can be concluded that all the components obtained can be converted into E_0 linear combination form of the standardized independent variable matrix A, therefore, F_0 can also be restored to a linear combination form about E_0, which can be summarized as:

$$F_0 = r_1E_0w_1 + .. + r_aE_0w_a + F_a$$

That is:

$$y^* = a_1x_1^* + \cdots + a_px_p^*$$

The regression coefficient corresponding to x_j^* in the above equation is:

$$a_j = \sum_{h=1}^{A} r_h w_{hj}^*$$

The corresponding parameter w_{hj}^* in the formula represents the j component of w_h^*. In summary, the process of multi-dependent variable modeling is obtained.

ARIMA model

First, for a time series, if it has the following properties, it is called a P-order autoregressive model, denoted as AR(p):

$$\begin{cases} Y_t = c + \varphi_1Y_{t-1} + \varphi_2Y_{t-2} + \cdots + \varphi_pY_{t-p} + \xi_t \\ \varphi_p \neq 0 \\ E(\xi_t) = 0; var(\xi_t) = \delta^2; E(\xi, \xi_t) = 0;\ \forall_s < t \end{cases}$$

Where Y_t is the observed value of variable Y at time t, c is the constant term, φ_p is the parameter of the model, and ξ_t is the error term.

If it has the following properties, it is called a Q-order moving average model, denoted as MA(q):

$$\begin{cases} Y_t = \mu + \zeta_t - \theta_1\zeta_{t-1} - \theta_2\zeta_{t-2} - \cdots - \theta_q\zeta_{t-q} \\ \theta_q \neq 0 \\ E(\zeta_t) = 0; var(\zeta_t) = \delta_\zeta^2; E(\zeta, \zeta_t) = 0;\ \forall_s \neq t \end{cases}$$

The above model requires the time series to have relatively strict stationarity, so for the unstable data, we introduce D-difference to make it become stable data, and then the above model can be used to predict. Let the sequence W_t = ΔY, after difference operation satisfy the condition of ARMA model, and its mathematical model is as follows:

$$W_t = \varphi_1W_{t-1} + \varphi_2W_{t-2} + \cdots + \varphi_pW_{t-p} + \zeta_1 - \theta_1\zeta_{t-1} - \theta_2\zeta_{t-2} - \cdots - \theta_q\zeta_{t-q}$$

According to the ACF and PACF graphs after difference, the p and q values in the model can be determined, and then they can be extended appropriately. After comparison and fitting, the optimal model can be selected.

Some of the models obtained by the above methods may not be very good, so further testing is needed. White noise test is carried out on the residual sequence of the fitted model. If it is white noise, it indicates that the information in the sample data has been extracted by the model completely and the fitting effect is good. The tested ARIMA model can then make predictions.

3.2.2. Data Preprocessing and Verification

We selected 11 indicators, including the number of pets, the number of pet families, the scale of pet economy industry, the penetration rate of pet families, per capita disposable income, Engel coefficient, population aging trend, the number of marriage registration, the size of pet market, the size of pet medical market, and the total value of pet food production, to evaluate the development of pet industry.

PLSR

Table 10 shows the information comprehensiveness of potential factors. Among them, the accumulated X variance represents the extraction of independent variable information, and the accumulated Y variance (R^2) represents the extraction of dependent variable information. The data shows that R^2 and adjusted R^2 are 0.967 and 0.956, respectively, with good fitting effect. This can be used to determine the maximum number of principal components of the parameter.

Table 10. Factor variance explanation table.

Latent factors	X variance	Cumulative X variance	Y variance	Cumulative Y variance (R^2)	Adjusted R^2
1	0.876	0.876	0.967	0.967	0.956
2	0.1	0.976	0.019	0.986	0.973
3	0.018	0.994	0.014	1	1
4	0.006	1	0	1	
5	0	1	0	1	1

The summary table (Table 11) and visual image of VIP (Cumulative projected Importance, Figure 6) are shown below, which indicates the explanatory importance of X to Y when the number of components is different and can also be used as a reference for the maximum number of principal components. For independent variables with a large VIP (greater than 1), it plays a relatively greater role in explaining the underlying factors (and thus the dependent variables).

Table 11. VIP summary table of independent variables.

variable	Factor1	Factor2	Factor3	Factor4	Factor5
Pet Market Size (USD bn)	1.067	1.066	1.05	1.05	
Number of pet families in China (10,000 households)	1.083	1.08	1.083	1.083	
China's pet economy industry scale (100 million yuan)	1.067	1.056	1.05	1.05	
Pet household penetration rate in China	1.086	1.079	1074	1.074	
China Resident pet pre Capita Disposable income (RMB)	1.078	1.068	1.061	1.061	
Engel coefficient	0.573	0.685	0.681	0.681	
Chinese Population Aging Trend (10,000 people)	1.001	0.992	1.005	1.005	
Number of Marriage Registrations in China (10,000 couples)	0.847	0.847	0.871	0.871	
Pet medical market size (100 million yuan)	1.056	1.046	1.039	1.039	
China's pet Food Gross Output Value	1.024	1.0166	1.017	1.017	

(10,000 yuan)	

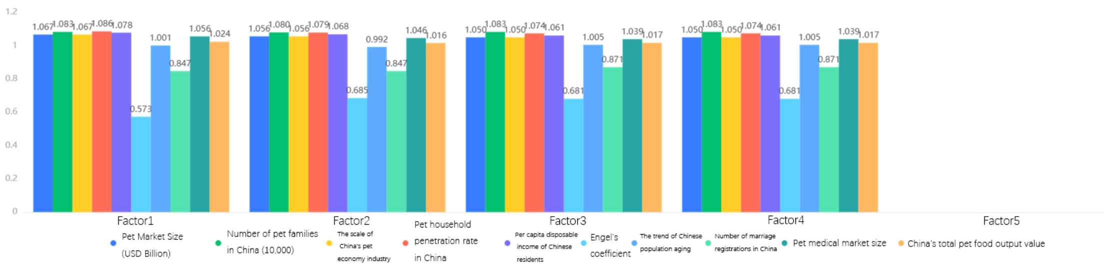


Figure 6. VIP diagram of the independent variable.

The component matrix table (Table 12) and factor load coefficient table (Table 13) after dimensionality reduction of principal component analysis can be obtained, and the importance of hidden variables in each factor can be analyzed.

Table 12. Ingredient matrix.

variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Pet Market Size (USD bn)	0.337	-0.046	0.103	-0.219	0
Number of pet families in China (10,000 households)	0.342	-0.322	-0.55	0.14	0
China's pet economy industry scale (100 million yuan)	0.337	-0.041	0.097	-0.238	0
Pet household penetration rate in China	0.344	-0.219	-0.262	-0.128	0
China Resident pet pre Capita Disposable income (RMB)	0.341	-0.114	-0.032	-0.049	0
Engel coefficient	0.181	0.859	0.404	0.223	0
Chinese Population Aging Trend (10,000 people)	0.316	0.084	0.577	-0.441	0
Number of Marriage Registrations in China (10,000 couples)	-0.268	-0.252	0.496	0.254	0
Pet medical market size (100 million yuan)	0.334	0.035	-0.025	0.382	0
China's pet Food Gross Output Value (10,000 yuan)	0.324	-0.155	0.272	0.636	0
Number of pets (10,000)	1.713	-0.812	-1.239	-0.15	0

Table 13. Factor load factor.

variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Pet Market Size (USD bn)	0.336	-0.088	0.131	-0.222	0
Number of pet families in China (10,000 households)	0.329	-0.124	-0.408	0.157	0
China's pet economy industry scale (100 million yuan)	0.336	-0.08	0.123	-0.241	0
Pet household penetration rate in China	0.335	-0.13	-0.158	-0.12	0
China Resident pet pre Capita Disposable income (RMB)	0.337	-0.109	0.022	-0.048	0
Engel coefficient	0.218	0.861	0.006	0.21	0
Chinese Population Aging Trend (10,000 people)	0.321	-0.148	0.553	-0.459	0
Number of Marriage Registrations	-0.279	-0.542	0.604	0.238	0

in China (10,000 couples)					
Pet medical market size (100 million yuan)	0.336	0.068	-0.053	0.383	0
China's pet Food Gross Output Value (10,000 yuan)	0.318	-0.297	0.323	0.627	0
Number of pets (10,000)	0.333	-0.158	-0.241	-0.029	0

Finally, the standardized formula of PLSR is as follows:

Number of pets (10,000) = 11008.8 + 98.97 × Pet Market Size (USD bn) + 286.69× Number of pet families in China (10 000 households) + 100.212 × The scale of China's pet economy industry (100 million yuan) + 210.854 × Pet household penetration rate in China + 137.508 × Per Capita Disposable Income of Chinese Residents (RMB) − 175.061 × Engel's coefficient − 33.228 × Aging Population of Chinese (10,000 people) − 172.563 × Number of Marriage Registrations in China (Pairs) + 98.302 × Pet medical market size (100 million yuan) + 47.266 × China's Pet Food Gross Output Value (10,000 yuan) (8)

- ARIMA

The SPSSPRO software was used to conduct ADF unit root test on Y_t, a time series often indicators from 2019 to 2023. The following takes the indicator of per capita disposable income as an example. The ADF unit root test results of this indicator are shown in Table 14 below.

Table 14. the ADF unit root test.

ADF Test Form							
variable	**Differential order**	**t**	**P**	**AIC**	**Threshold**		
					1%	5%	10%
PCDI	0	0.234	0.974	65.982	-7.355	-4.474	-3.127
	1	-6.729	0.000***	43.069	-10.417	-5.778	-3.392

Note:***,**, and* represent the significance levels of 1%, 5%,and 10%, respectively.

As can be seen from Table 14, the ADF unit root test p value of per capita disposable income time series Y_t is greater than 0.05, indicating that the null hypothesis is accepted in the 95% confidence interval, that is, the series Y_t is not stable.

The first difference of this time series is carried out, and the first difference series $Y_t = \Delta Y_t$, is obtained. As can be seen from Figure 5, the p value of the ADF unit root test of the first difference series Y_t is less than 0.05, indicating that the null hypothesis is rejected in the 95% confidence interval, that is, the series Y_t is stable.

The p value of the ADF unit root test of the sequence Y_t after the difference of the other nine indexes is also less than 0.05, so it is not necessary to go into details here

After the time series passes the stationarity test, it is necessary to test whether it is a white noise sequence. SPSS software is used to make the ACF diagram and PACF diagram of the sequence after first-order difference often indexes, as shown in Figure 7,and Models 1 — 10 in Figure 7 and Figure 8 represent the number of pets, the number of pet households, the size of the pet economy, the penetration rate of pet households, and per capita Disposable income, Engel coefficient, population aging trend, number of marriage registrations, pet market size, pet medical market regulation model. It is found that the P-value of all order white noise tests is less than 0.05, indicating that the sequence passes the white noise test under 95% confidence interval, that is, the sequence Y_t after the first difference is a stationary non-white noise sequence, which is suitable for ARMA model.

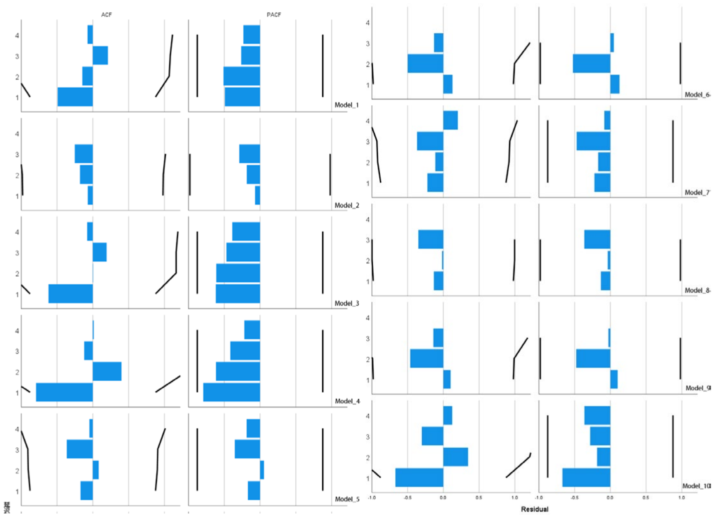


Figure 7. ACF/PACF plot after differential indicator.

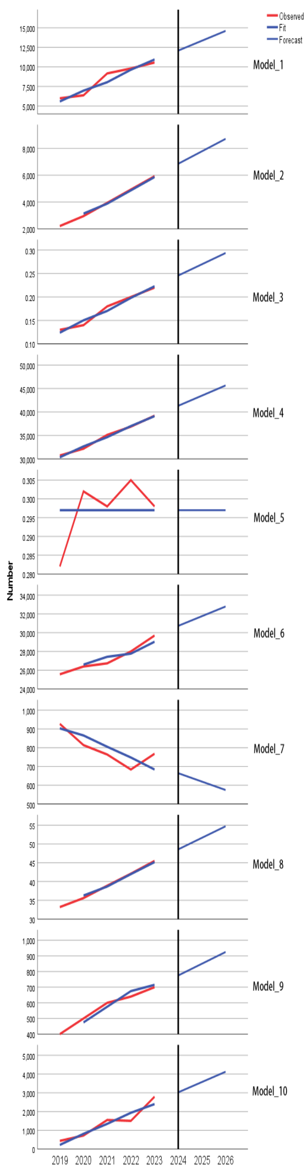


Figure 8. foreast results of the indicator.

3.2.3. ARIMA ModelFitting

As mentioned above, the sequence Y_t after first-order difference is a stationary non-white noise sequence, which is suitable for ARMA model. Then, SPSS software is used to automatically select the corresponding p and q values, and ARMA model is used to predict all the above ten indicators, and the prediction results often indicators after 2024 to 2026 can be obtained, as shown in Figure 8.

After that, the correlation test of the above indicators is carried out. The correlation matrix heat maps (Figure 9) of pet related indexes in China are made by MATLAB.

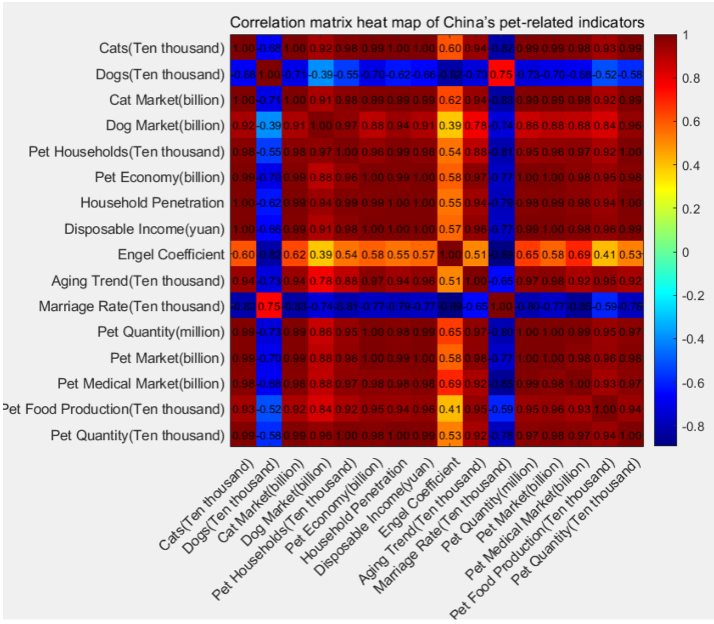


Figure 9. Correlation heat map.

3.2.4. Results and Analysis

We predict the development trend often indicators in 2024-2026 through ARMA model and substitute them into equation (8) to obtain the number of pets in 2024-2026.

In summary, we get the predicted value:

In 2024, the total number of cats and dogs in China will be 140.1028 million. In 2025, the total number of cats and dogs in China will be 1,523,921 million. In 2026, the total number of cats and dogs in China will be 165.8699 million;

Statistics show that the number of pet cats and dogs in China is on the rise, with an annual growth rate of 7% to 8%, reflecting the expansion of the development scale of China's pet industry.

Multiple factors support the long-term growth of China's pet industry

Human-pet relationship

The relationship between people and pets has become increasingly intimate, and pets have become an emotional outlet in the era of internal volume. Pets provide emotional value and rich life value. In the post-epidemic era, people pay more attention to pets accompanying their families and are more eager for pets to enrich their lives.

Consumption consciousness

According to the "2023 China Pet Industry Trend Insight White Paper", after the release of the epidemic, nearly 25% of pet owners said that the cost has increased, and more than 30% of pet owners said that the consumption frequency has increased. Pet owners spend more because they pay more attention to pet health, food safety, travel with pets, carpe diem, compensation psychology and other reasons.

Economic growth

The increase in the number of pets combined with the increase in per capita disposable income of residents is positively driving the strengthening of pet consumption. Household disposable in-come provides a solid material basis for pet rearing. Since 2016, the per capita disposable income of Chinese residents has been growing steadily year by year. Although the per capita disposable in-come growth rate has fluctuated, the overall trend is rising, and the consumption power of residents has increased accordingly, which provides a broad room for growth for the development of the pet consumption market. The consumption concept and consumption level of pet raising groups are upgraded towards higher quality and can bear higher pet raising costs. It is beneficial to the rapid growth of the industry market size.

Population structure

Affected by the change of China's social and demographic structure, China's pet market still has a large room for growth. " China Pet Products Consumption Trend Report" mentioned in A, with the change of China's population structure, the number of "empty nesters" and "young people living alone" has increased, and the demand for pet companionship has been rising, and this group has gradually become the main consumption force of the pet economy. According to the official data of the National Bureau of Statistics, as of the end of 2022, China's population of 60 years old and above is 280 million, of which empty nesters account for more than half, and even more than 70% in some areas, and the elderly population is increasing and the aging trend is obvious; At the same time, the change of young people's migrant work, job hunting and marriage and love has led to the decline of young people's willingness to marry and have children. In 2013, China's solitary population was about 70 million, and by 2022, the number has increased rapidly to nearly 150 million, an increase of about 8%.

Behind the huge single groups and elderly groups, is the emotional need of" group loneliness".

As a partner,"pets" can provide companionship and other positive emotional values, eliminate people's pressure in work and life, and reduce loneliness. The status of" pets" in the minds of pet raising groups is gradually rising, bringing new consumer markets and consumer demand for the development of pet industry.

Therefore, although these components did not account for too high a proportion in the previous analysis, there is no denying that the growing pet industry is closely related to the demographic changes in today's society.

4. Question 2: Global Pet Industry Development and Demand

On a global scale, especially in the US and European markets, based on historical data on the number of pets and the size of the pet food market, the market demand relationship between different countries is analyzed using panel data models. Based on the number of overseas pet cats and dogs in the appendix and relevant data collected from other countries, the paper makes a comprehensive analysis of the development of the global pet industry with the help of gray prediction and ARIMA model. At the same time, we made a pie chart of the global market share of pet food demand in China, the United States, France and Germany, and discussed the changes in global pet food demand with these four countries as representatives.

4.1. Model Building and Visualization

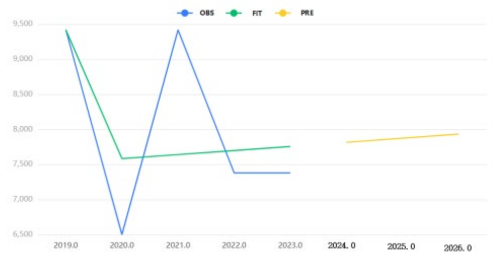
4.1.1. Global Pet Industry Development

The global pet industry is also analyzed by the number of cats and dogs. Using the data given in the appendix, SPSS and grey prediction model, we give the curve of pet population change in the United States, France and Germany. In addition, based on the collected cat and dog populations in Japan and France, the ARIMA model was used to fit together and predict future changes.

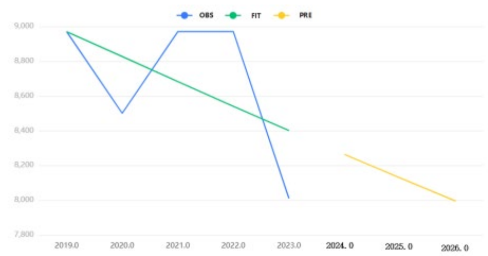
Since the interpretation and establishment of grey prediction and ARIMA model have been given in the first question, the relevant knowledge will not be repeated here.

- Grey prediction

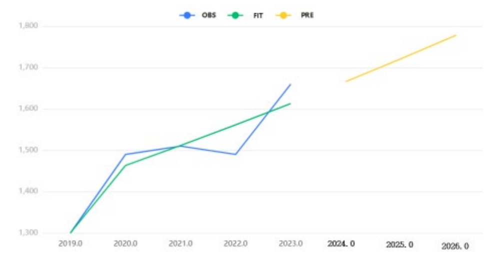
After all the data passed the level ratio test, combined with the gray prediction model solving method in the first question, the cat and dog gray prediction model fitting curves of the United States, France and Germany (Figure 10)were drawn respectively as follows, and Pictures (1) — (6) in Figure 10 represent Pet cat forecast chart in the United States, Pet dog forecast chart in the United States, France pet cat prediction chart, France pet dog prediction chart, Germany pet cat prediction chart and Germany pet dog prediction chart.



(1) Pet cat forecast chart in the United States.



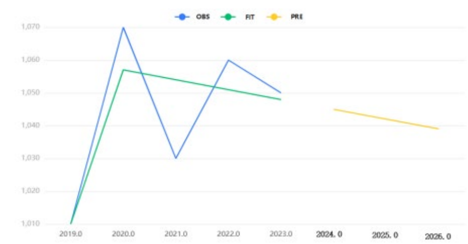
(2) Pet dog forecast chart in the United States.



(3) France pet cat prediction chart.

(4) France pet dog prediction chart.

(5) Germany pet cat prediction chart.



(6) Germany pet dog prediction chart.

Figure 10. gray prediction model fitting curves of the United States, France and Germany.

As can be seen from the above picture:

The number of cats and dogs in France has a relatively obvious growth trend, showing that the French cat and dog breeding market has greater potential.

Although the number of cats and dogs in the United States is significantly higher than in France and Germany, the erratic growth rate reflects the volatility of the American cat and dog breeding market.

The number of cats and dogs in Germany did not fluctuate much, but the overall trend was slow to decline, showing that the German cat and dog breeding market is relatively saturated.

ARIMA fitting

For the number of cats and dogs collected in Japan and the United Kingdom, ARIMA model was used for fitting prediction:

First, the ADF unit root test was carried out on the number of cats and dogs in the two countries respectively, the results are shown below as Table 15, Table 16, Table 17 and Table 18.

Table 15. ADF Test Form (Japanese Cats).

variable	Differential order	t	P	AIC	Threshold
Cat	0	0.428	0.983	71.213	-4.939, -3.478, -2.844
Cat	1	-9.814	0.000***	42.733	-5.354, -3.646, -2.901
Cat	2	-11.137	0.000***	68.202	-5.354, -3.646, -2.901

exegesis:*** 、** represent significance levels of 1% and 5%,respectively.

Table 16. ADF Test Form (Japanese Dogs).

variable	Differential order	t	P	AIC	Threshold
Dog	0	-3.146	0.023**	93.348	-4.332, -3.233, -2.749
Dog	1	-1.936	0.315	82.923	-4.665, -3.367, -2.803
Dog	2	-4.471	0.000***	84.285	-5.354, -3.646, -2.901

Table 17. ADF Test Form (UK Cats).

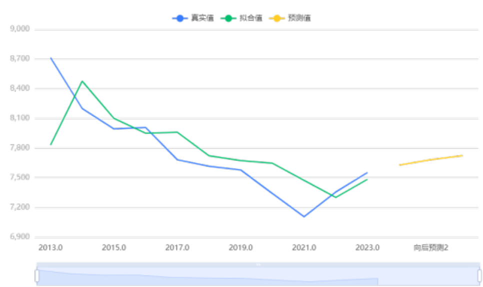
variable	Differential order	t	P	AIC	Threshold
Cat	0	-0.094	0.950	89.362	-4.939, -3.478, -2.844
Cat	1	-4.949	0.000***	66.417	-5.354, -3.646, -2.901
Cat	2	-2.044	0.268	83.847	-5.354, -3.646, -2.901

Table 18. ADF Test Form (British Dogs).

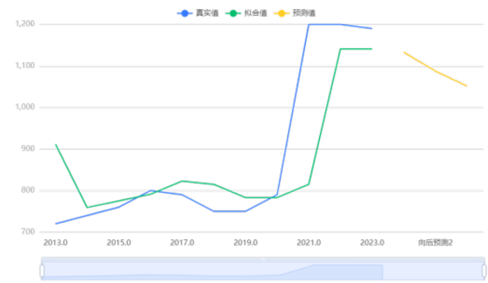
variable	Differential order	t	P	AIC	Threshold
Dog	0	3.068	1.000	84.438	-4.665, -3.367, -2.803
Dog	1	1.567	0.998	76.476	-5.354, -3.646, -2.901
Dog	2	-3.85	0.002	79.918	-4.939, -3.478, -2844

From the above four tables, it can be seen that Japanese pet cats and dogs and British pet cats and dogs pass the test when the difference order is 1, 2, 1 and 2 respectively. Then, the SPSS system was used to automatically find the optimal parameters p and q based on AIC information criteria, and the ARIMA model was constructed at the same time. Four fitting prediction curves (Figure 11) were obtained as follows, and Pictures (1) — (4) in Figure 11 represent the Japan pet cat prediction chart, the Japan pet dog prediction chart, the UK pet cat prediction chart, and the UK pet dog prediction chart, respectively.

(1) Japan pet cat prediction chart.



(2) Japan pet dog prediction chart.



(3) UK pet cat prediction chart.

(4) UK pet dog prediction chart.

Figure 11. fitting prediction curves.

4.1.2. Global Demand for Petfood

We collected pet food spending in China, the United States, France and Germany, and Figure 12 showed their share of the global pet market with the help of a pie chart.

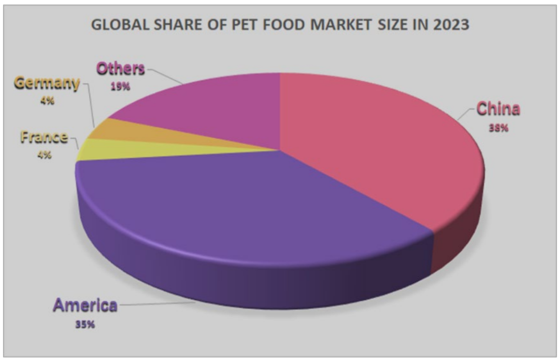
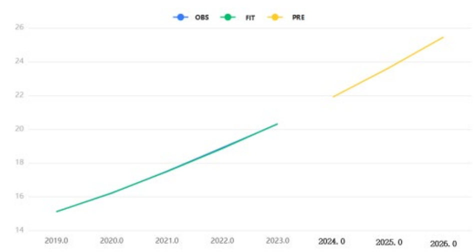


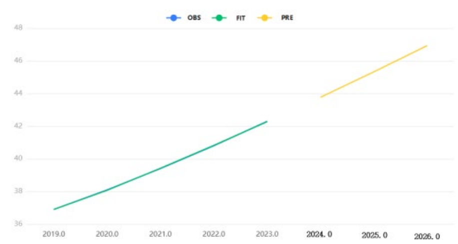
Figure 12. Pet food market share by country.

As can be seen from the figure, the pet food market share of the above four countries accounts for about 80% of the world's total, so the changes in global pet food demand can be predicted based on the pet food spending of these four countries.

Also using the grey prediction model, we give the food expenditure fitting forecast curve for four countries in Figure 13, and Pictures (1) — (4) in Figure 13 represent Fitting diagram of China's pet food expenditure, Fitting diagram of U.S. pet food spending, Fitting forecast map for France , Fitting forecast map for Germany, respectively.

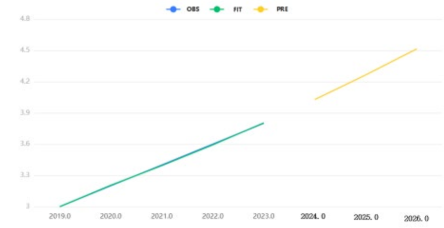


(1) Fitting diagram of China's pet food expenditure.



(2) Fitting diagram of U.S. pet food spending.

(3) Fitting forecast map for France.



(4) Fitting forecast map for Germany.

Figure 13. Food market forecasts for four countries.

As shown in the chart above, the market size forecast values of China and the United States are significantly higher than those of France and Germany, indicating that their market potential and consumption scale are larger, and the market size forecast of each country will increase significantly in 2026 compared with 2024.

As can be seen from the forecast results, the pet food market is expected to grow in all coun- tries in the next few years, with more significant growth likely to be observed in the Chinese and American markets. This represents an increase in global pet food demand over the next three years.

5. Question 3: Development of Pet Food Industry in China

We collected the global pet food expenditure data of the past five years, combined with the global pet market demand in question 2, used Lasso model to fit the output and export volume of pet food in China, and combined with MATLAB to predict the global pet food demand in the next three years.

5.1. Model Building and Visualization

We selected global pet food expenditure, China's population growth (annual percentage), China's total fertility rate (number of births per female), China's per capita GDP (current USD) and China's pet medical market size (RMB 100 million) as independent variables (Figure 13), and the two dependent variables were the output and export volume of pet food in China, respectively, and applied Lasso model to fit.

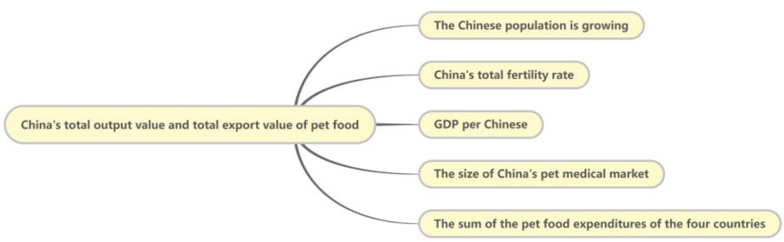


Figure 13. Factors influencing China's pet food production and exports.

Lasso regression is mainly to solve the problems of overfitting and model instability encountered by traditional linear regression when dealing with high-dimensional data. Lasso penalizes the absolute value of the coefficients by introducing an adjustment parameter λ, forcing some unimportant coefficient values to zero, which not only automatically selects important features, but also effectively controls the complexity of the model.

The mathematical expression of Lasso regression can be expressed as:

$$Lasso = \min_{\beta}\left\{\frac{1}{2n}\sum_{i=1}^{n}(y_i - x_i^T\beta)^2 + \lambda\|\beta\|_1\right.$$

Where y_i is the true value of the it's sample, β is the regression coefficient, x_i is the predictor matrix, λ is the penalty coefficient, which is used to balance the fitting error and model complexity, and n is the number of samples. Our aim is to find the value of the Lasso function described above.

The usual Lasso problem is solved by using coordinate descent method, gradient descent method or least Angle regression method, and gradually approximates the optimal solution through iterative optimization.

Firstly, the λ value in the formula is determined by cross-validation method. Using MATLAB, the following Lasso regression cross-validation diagram is drawn.

In the figure above, the abscissa is the logarithmic value of λ, and the ordinate is the model mean square error. Through analysis, λ values corresponding to the output and export volume of pet food in China can be obtained as follow: $\lambda_{\text{output}} = 2.462$, $\lambda_{\text{export}} = 2.024$

In order to quantitatively express the relationship between the independent variable global pet food expenditure and the two dependent variables China pet food production and export volume, a prediction formula Figure 14 was constructed:

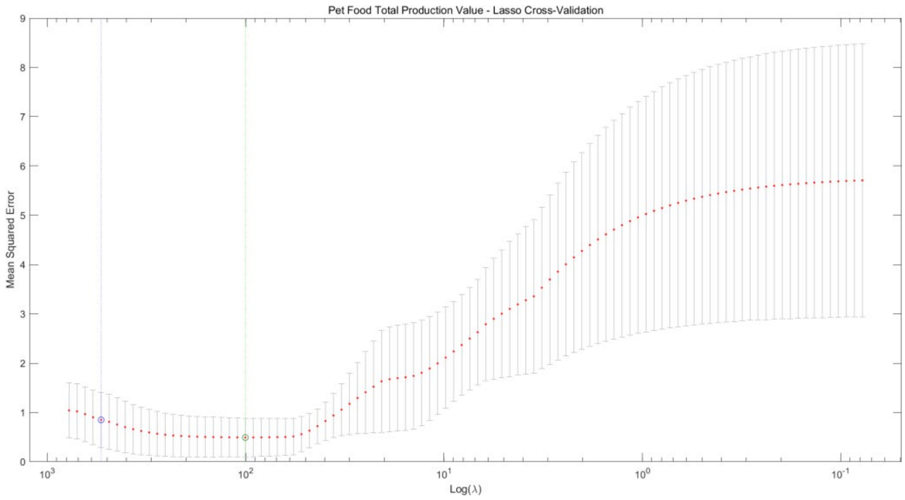
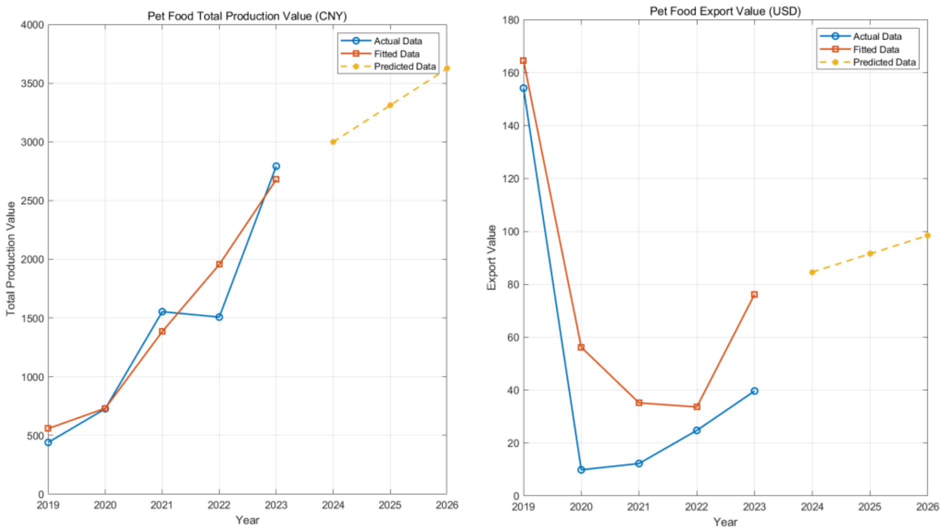


Figure 14. Cross-validation result graph.

$$Y_{production} = \beta_1^T X_{expenditure}^T + b_1$$
$$Y_{\text{export volume}} = \beta_2^T X_{expenditure}^T + b_2$$

Where β is the regression coefficient, bis the intercept, $Y_{\text{export volume}}$, $Y_{production}$ are the predicted export volume and output respectively.

Then MATLAB was used to fit the Lasso model, and combined with the above formula to predict the changes in the next three years, the following fitting prediction curve of China's pet food output and export volume (Figure 15) was obtained:



Forecast map of production value fitting **Export volume fits the forecast chart.**

Figure 15. fitting prediction curve of China's pet food output and export volume.

5.2. Result Analysis

As can be seen from Figure 13, although pet food production in 2022 has slightly decreased, the overall trend is relatively obvious. And the predicted values in the next three years are 3000.12, 3311.91, 3623.70, respectively, with an obvious growth trend.

As can be seen from Figure 14, the export volume of pet food in China in 2020 fell sharply compared with that in 2019, which may be due to the decline in global transaction volume caused by the outbreak of "epidemic". However, the number of exports showed a gradual upward trend in the following years, indicating that the impact of the epidemic was gradually reduced. Finally, the export volume forecast for the next three years is 84.5665, 91.4894, 98.4124, showing recovery growth.

Based on the data of China's pet food production and export volume for 8 years each, it is predicted that food production will increase significantly in the next few years, while export volume will show recovery growth. From these trends, it can be seen that China's pet food industry will show steady growth in the next few years.

6. Question 4: Sustainable development of pet food industry in China

China's pet food industry will inevitably be affected by the foreign economic policies of Euro-pean and American countries. We collected the pet food export value data of Chinese mainland and Taiwan Province from January 2015 to October 2024 and took the foreign economic policy of the United States as an exogenous impact event, and analyzed the impact of the policy on the two places by using the seasonal ARIMA model.

6.1. Model building

original three variables, three hyperparameters (P, D, Q) and a seasonal cycle parameter s are introduced, where P, D and Q respectively represent the order of seasonal autoregression, the order of seasonal moving average and the number of seasonal differences, and s represents the cycle length.

The specific formula of seasonal ARIMA model is as follows:

$$\varphi_p(B)\varphi P(B_s)(1-B_s)^d(1-B_s)^{Dxt} = \theta_q(B)\Theta_Q\ (B_s)\epsilon_t$$

here B is the delay operator, B_S Is the seasonal delay operator, ϕ_P (B)、θ_q (B)are seasonal multinomial delay operators. Therefore, this seasonal ARIMA model is actually to make D-order seasonal difference (deperiodic) and D-order constant difference (detrended) for a time series $\{x_t\}$ with seasonal characteristics to get a new sequence $\{y_t\}$, When P = D = Q = 0, the seasonal ARIMA model degenerates into an ordinary ARIMA model.

6.2. Model Visualization

First, clean the data. The collected pet food export values of Chinese mainland and Taiwan Province were summarized at quarterly intervals, and outliers were removed by Z-score method.

Then, the ADF unit root test is performed on the data of Chinese mainland and Taiwan Province respectively.

As can be seen from Table 19 and Table 20, the *p*-value of Chinese mainland and Taiwan Province after two and one difference respectively is much less than 0.05, indicating that the null hypothesis is rejected in the 95% confidence interval, and both of them pass the ADF unit root test.

Table 19. Chinese mainland ADF unit root test results.

Differential order	variable	*t*-Value	1% Threshold	5% Threshold	10% Threshold	*p*-value
0	P	-0.182	-3.508	-2.890	-2.580	0.9406
1	D1	-3.103	-3.509	-2.890	-2.580	0.0263
2	D2	-2.890	-2.580	-1.950	-1.610	0.0000
3	D3	-2.580	-1.950	-1.610	-1.290	0.0000

Table 20. Taiwan ADF unit root test results.

Differential order	variable	*t*-Value	1% Threshold	5% Threshold	10% Threshold	*p*-value
0	P	-1.386	-3.508	-2.890	-2.580	0.5890
1	D1	-3.897	-3.509	-2.890	-2.580	0.0021
2	D2	-6.875	-3.509	-2.890	-2.580	0.0000
3	D3	-7.763	-3.509	-2.890	-2.580	0.0000

After the time series is tested by ADF, the ACF and PACF charts of the two are drawn by SPSS respectively to test whether the two are white noise sequences (Figure 16 and Figure 17).

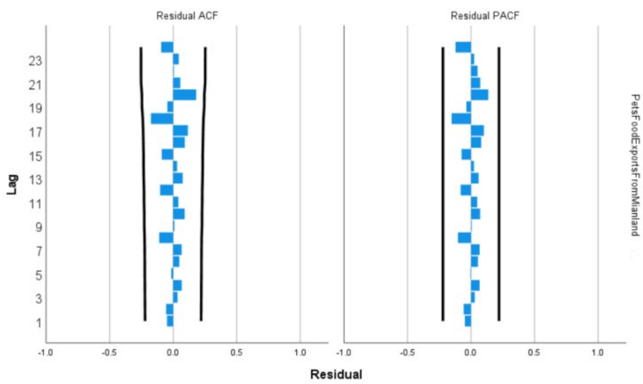


Figure 16. ACF/PACF diagram of Chinese mainland.

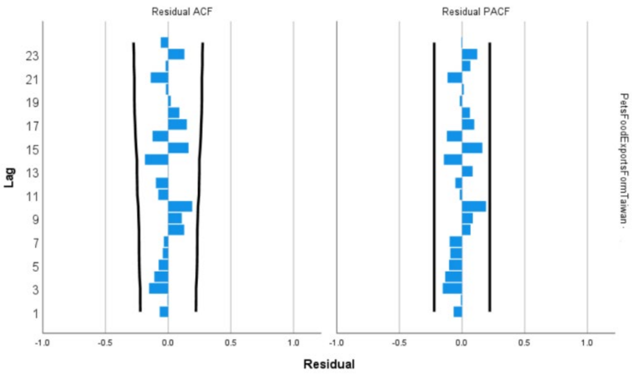
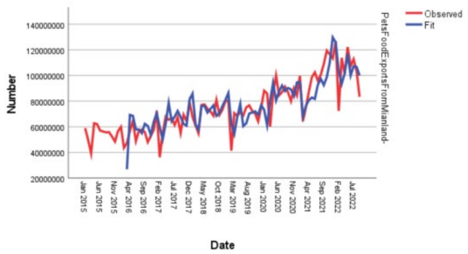
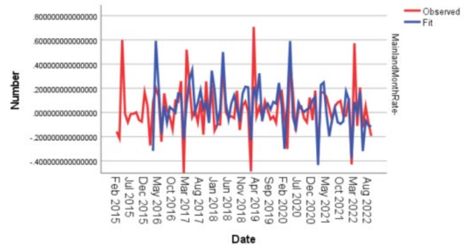


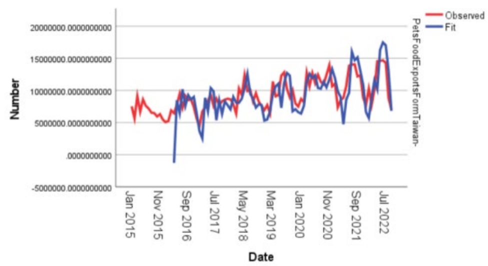
Figure 17. ACF/PACF diagram for Taiwan, China.

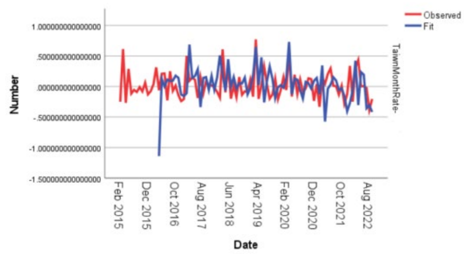
It can be seen from the image that all the data are stationary non-white noise sequences, and through analysis, the seasonal ARIMA model parameters of Chinese mainland are (3,2,3) (1,1,1,), and the seasonal ARIMA model parameters of Taiwan Province are (1,1,1) (1,1,1), and according to the analysis, the seasonal period s is 12. Then, through the seasonal ARIMA model, the seasonal fitting curve and the monthly growth rate fitting curve of the two export values (**Figure 18**) were obtained:





(1) Seasonal fit curve of mainland export value. (2) Seasonal fit curve of the continental monthly growth rate.





(3) Seasonal fit curve of Taiwan's export value. (4) Seasonal fitting curve of Taiwan's monthly growth rate.

Figure 18. seasonal fitting curve and the monthly growth rate fitting curve.

As can be seen from the figure, on the whole, the export value will show seasonal cyclical changes, and a similar change rule will appear every other year or so, and the peak value of export volume generally occurs from November to March of the following year. However, around March 2018, the mainland's exports should have had a peak season (compared with Taiwan), but it was not obvious, and in 2018, Sino-US trade friction intensified, this abnormal data may be due to the increase of tariffs on Chinese goods in 2018. The increase from the original 15% to 25%, so it can be inferred that the increase in tariffs will not be conducive to the growth of Chinese food exports.

6.3. Sustainable Development Policy Recommendations

The sustainable development of China's pet food industry is affected by many factors. Based on the four issues discussed and analyzed above, the following suggestions can be put forward for the formulation of its strategy.

Market segmentation for different pet types (such as cats, dogs) and development of specialized product lines. From the analysis of the previous two questions, it can be concluded that most of the market shares of the pet market in China and even in the world are occupied by cats and dogs. Therefore, market segmentation can optimize the structure of the pet food industry, reduce unnecessary investment, and promote the development of the industry.

Focus on the high-end market and develop high value-added products. According to the results of the fourth question, foreign economic policies and tariffs will affect the export volume of pet food in China. Therefore, we can try to develop high value-added products while maintaining a high export price, and maintain a high income even in the face of a higher tariff rate.

Expand international sales channels and seize international market share. According to the analysis of the second Question, China's international pet food market share is roughly the same as that of the United States. We can try to establish a perfect online sales channel or establish a partnership with local distributors and retailers. At the same time, we can take advantage of the preferential tariff policies in international trade agreements to seize international market share and constantly improve the international competitiveness of China's pet food industry.

7. Model Evaluation

7.1. Strengths

Combined with the Chinese social background, this paper analyzes the internal relationship between the" group loneliness" emotion behind the aging population, the decline of marriage rate, and the change of marriage and love, and the "pet companion" and "the development of China's pet industry" from a social perspective.

The comprehensive use of gray prediction, partial least squares regression, ARIMA, seasonal ARIMA and other mathematical models is conducive to a comprehensive analysis of the problem. In the process of solving the model, the auxiliary methods such as quadratic exponential smoothing, linear regression and ADF unit root test are used to test the model, and the model results are verified from various aspects. The accuracy of the model is improved.

The seasonal ARIMA model is used to analyze the periodic changes of pet food export value. The third question uses LASSO model to solve possible overfitting or model instability problems, which reflects the rigor in data processing.

7.2. Improvement Needed

Although many indicators have been collected, some indicators are missing and insufficient, so the results of model fitting cannot be completely consistent with the real situation.

Although we have synthesized many models and improved the accuracy of the models, too many models also lead to complicated solving process and cumbersome steps, and it is impossible to quickly and accurately determine the choice of parameters.

7.3. Future Work

Our model still has some flaws. In the process of data processing, due to the small amount of data collected, the degree of fitting of some models is poor, and even some models cannot be used. Therefore, we hope to use a more detailed database to complete a more accurate assessment of China's pet industry and its related derivative industries, so that our method can be truly helpful to the relevant departments. In this scheme, in addition to using mathematical models for fitting, we also analyze from another Angle through sociological methods. In the future, we hope that we can have a deeper understanding of the relevant sociological knowledge and make a deeper explanation and analysis of the mathematical model.

The continuous development of the pet industry is only one of the driving forces for the continuous stake-off of China’s economy. I believe that in the near future, under the joint efforts of our Party and the people, there will be more and more rapid development of Chinese industries. We believe that the rapid development of China’s pet industry predicted in this plan is only a microcosm of China’s rapid economic development, and China’s economic development is bound to have a bright future. With the popularity of” pet companions”, problems such as ”empty nesters” and ”lonely groups” brought about by the aging population of Chinese society will also be further solved.

8. Conclusion

This study provides a comprehensive analysis of the development trends and influencing factors of China's pet industry by integrating multiple mathematical models and sociological perspectives. The findings suggest that demographic shifts, including an aging population and declining marriage rates, are key drivers behind the growing demand for pet companionship. By employing forecasting techniques such as ARIMA, seasonal ARIMA, and LASSO regression, the study enhances the accuracy of industry trend predictions and offers insights into the sustainability of pet-related businesses.

Despite the robustness of the modeling approach, data limitations and the complexity of model selection remain challenges. Future research should incorporate more extensive datasets and refine modeling techniques to improve predictive accuracy. Additionally, interdisciplinary perspectives, particularly from sociology and behavioral economics, could provide deeper insights into consumer behavior and market dynamics.

Overall, the continued growth of China’s pet industry reflects broader social and economic transformations. As the industry evolves, stakeholders — including businesses and policymakers — must adapt to emerging trends to support sustainable development and meet the changing needs of consumers.

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