

Multimodel Forecasting and Sustainable Strategy Development for China's Pet Industry in a Global Context

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Abstract: The global pet industry has experienced rapid expansion, creating an urgent need for comprehensive market analysis and forecasting to guide strategic decision-making and resource allocation. This study provides a multifaceted examination of pet industry development, with particular focus on China's market dynamics and global integration. The analysis employs advanced visualization techniques, including area charts, line graphs, and pie charts, to examine the evolution of China's pet industry by species over a five-year period. Key growth drivers are identified, including household penetration rates, owner demographics, and macroeconomic factors. ARIMA modeling projects populations of 67.63-64.33 million cats and 52.89-52.95 million dogs over the next three years. Globally, 3D stereograms and comparative charts reveal species-specific growth patterns. GM(1,1) modeling forecasts pet food sales reaching 133.96-154.69 billion in the coming three years. For China's pet food sector, ensemble regression models predict domestic production values of 235.7-281.9 billion yuan, while linear regression estimates exports at 26.3-33.7 billion yuan. A novel analytical model quantifies effects of tariffs, exchange rates, trade barriers, and infrastructure on exports. The framework provides both predictive analytics and sustainable development strategies. These findings offer valuable insights for stakeholders across the pet industry value chain, while contributing methodological advances to academic literature on market forecasting and industry analysis.

Keywords: ARIMA; GM (1,1); LinearRegression; ElasticNetCV; XGBRegressor; VotingRegressor; Custom Function Prediction Model

1. Introduction

1.1 Problem Background

Driven by economic development and changing consumer habits, the pet industry has become a fast-growing global sector. In China, milestones such as the establishment of the China Small Animal Protection Association and the entry of international pet brands into the domestic market have accelerated this growth. Demographic changes, including an aging population and the increasing prevalence of DINK families [1], have further popularized the concept of 'pet companionship' and driven the expansion of related industries such as pet food, clinics, supplies and care services [2]. However, the increasing number of urban pets, especially dogs, has brought with it a number of challenges. Policies such as dog registration and licensing have been implemented to address issues such as disease transmission and waste management [3]. In addition, international developments- such as changes in trade policy under US President Trump- have affected import and export tariffs on pet products [4]. These factors highlight the importance of developing time-series forecasting models and strategic recommendations for the sustainable growth of the pet industry.

1.2 Literature Review

The global pet industry is undergoing profound transformation, with rising economic levels and shifting social structures jointly driving market expansion. Research indicates that rising per capita GDP significantly boosts pet consumption capacity, while the rise of the singles economy and aging trends fuel demand for emotional companionship. This has propelled China's pet household penetration rate from 14% in 2019 to 22% in 2023. This growth is accompanied by a shift in species preference, with cat ownership surpassing dog ownership

for three consecutive years, reflecting how urbanization reshapes consumer choices.

Forecasting methods are trending toward multi-model integration. ARIMA models enhance efficiency through automated upgrades, achieving an error rate below 5% in pet population forecasting. The Grey Prediction Model GM (1,1) successfully extrapolates global pet food sales growth trajectories but requires machine learning integration to strengthen variable interaction analysis. Ensemble learning frameworks combining linear regression and XGBoost algorithms achieve high accuracy in forecasting China's pet food output value, while policy quantification models precisely measure tariff elasticity and exchange rate threshold effects.

International policies significantly impact the industrial chain. Tariff hikes in Europe and the US directly reduce export volumes, while trade barriers increase compliance costs, driving market shifts toward Southeast Asia. Profit sensitivity surges when exchange rate fluctuations exceed the 6.9 threshold, and infrastructure optimization can shorten delivery cycles. Existing research faces three limitations: inadequate response to sudden events, lack of ecological footprint quantification, and lagging application of advanced algorithms.

This paper innovatively constructs a "Prediction-Policy-Sustainability" three-dimensional framework: synergistically optimizing prediction models, developing policy impact simulation modules, and establishing a green supply chain system integrated with blockchain technology. This provides the industry with solutions that balance economic resilience and environmental sustainability.

1.3 Problem

1.3.1 Problem 1:

To analyze the development of China's pet industry by type of pet over the past five years based on the data collected. To predict the future development of China's pet industry by analyzing the factors that have contributed to the development of China's pet industry.

1.3.2 Problem 2:

The development of the global pet industry by pet type is analyzed and a mathematical model is developed to forecast the global demand for pet food over the next three years.

1.3.3 Problem 3:

Analyze China's pet food industry based on the data. Then combine the global trend of pet food demand per hour and China's development to forecast the production and export of pet food in China over the next three years.

1.3.4 Problem 4:

Based on collected data, quantitatively analyze the impact of new foreign economic policies (such as tariff policies) in Europe and the United States, and develop a mathematical model to formulate a feasible strategy for the sustainable development of China's pet food industry.

2. Model and Solution for Problem 1

2.1 Analysis of China's Pet Industry Development by Pet Type

The Chinese pet industry has undergone significant growth and diversification over the past five years. Figure 1. and Figure 2. illustrate the specific trends in the development of the pet population, with a focus on dogs and cats, as well as other types of pets.

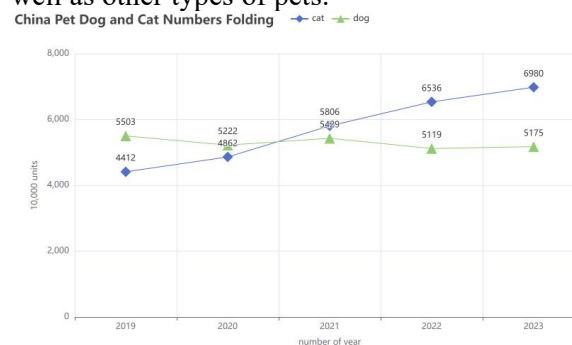


Figure 1. China's Pet Dogs and Cats Population

According to the Figure 1. line graph, the number of both pet dogs and pet cats in China shows a steady growth from 2019 to 2023 as the pet market continues to expand. However, the number of pet dogs in 2023 decreases rather than increases compared to 2019. In contrast, the number of pet cats is growing slightly faster and will exceed the number of pet dogs for the third consecutive year.

Figure 2. reverse bar chart shows the favourite pet types among Chinese urban households from 2019 to 2021. Among them, cats and dogs are the most popular pet types.

2.2 Analysis of Pet Industry Development Factors

Pets live with people, they participate in people's everyday life activities and are often

seen as human-like family members. Therefore, the pet industry and its owners can be considered as a cohesive consuming unit [5]. Permeability is a measure of the proportion or degree of participation in an activity among a particular group. In the pet industry, the level of Permeability can intuitively reflect the popularity of the industry, the development trend and the size of the potential market. Here's the formula for calculating household Permeability for pet dogs and cats [6].

$$\text{Permeability} = x \div (y \div z) \quad (1)$$

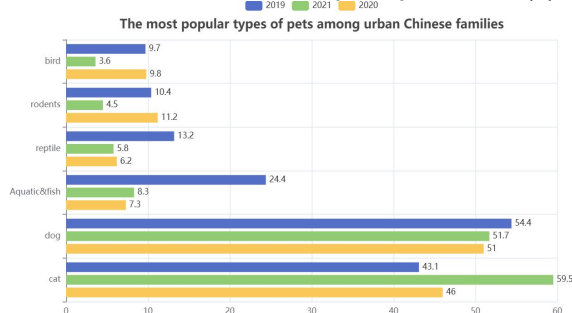


Figure 2. The Most Popular Types of Pets among Urban Chinese Families

2019-2023 Penetration Rate of Pet-Raising Households in China

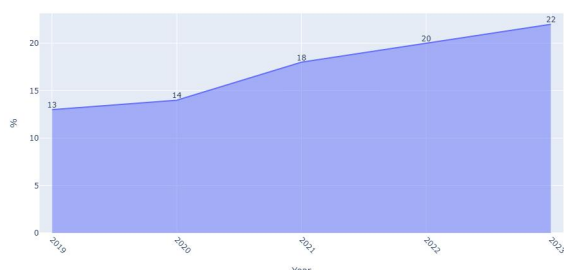


Figure 3. Permeability of Households with Pets in China

Permeability of pet-keeping households in China has continued to climb from 2019 to 2023, according to data from the Area Map of Pet-keeping Household Penetration in Figure 3., highlighting the fact that the act of pet-keeping is increasingly becoming a new lifestyle choice for many families [7].

According to the trends revealed in the Pet Industry White Paper 2023 and Figure 4, China is experiencing continued growth in the number of people living alone, and it is particularly notable that singles in the 21-30 age group are the mainstay of pet ownership [8].

Form Figure 5, over the past decade China's economic development has shown a solid and upward trend. With the steady growth of the domestic economy and rising per capita income, people's living standards have also improved significantly.

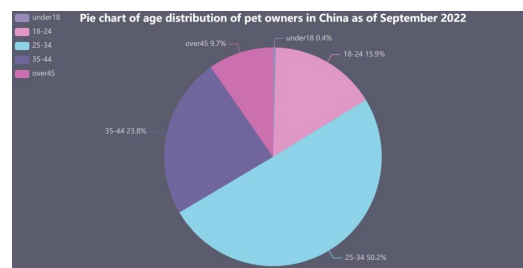


Figure 4. Age distribution of pet owners in China

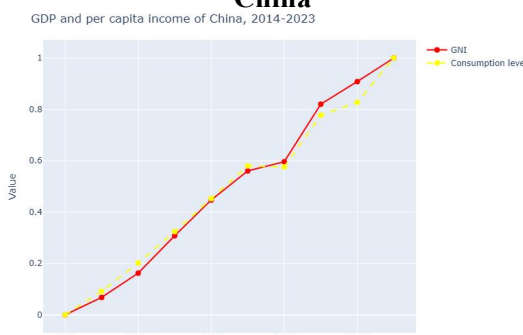


Figure 5. Line graph of GDP and per-capita income

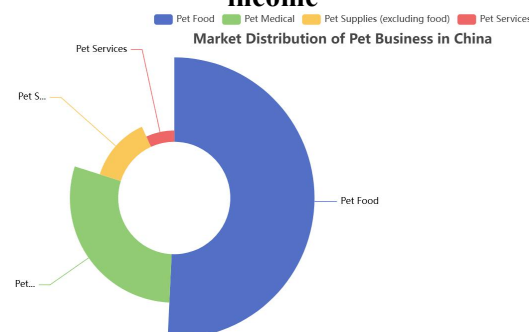


Figure 6. Market Distribution of Pet Business in China

Figure 6. the rose pie chart illustrates the market distribution of the Pet Business in China. As can be seen from the figure, pet food occupies the largest market share [9].

2.3 Prediction Model: The ARIMA Algorithm

Data from the number of pet dogs and cats in China and the permeability of pet-owning households in China, 2019-2023.

Forecasting the development of China's pet industry in the next three years based on the ARIMA algorithm.

The ARIMA model is first developed.

The essence of ARIMA model is the combination of difference operation and ARIMA model, denoted as ARIMA (p, d, q).

The ARIMA model can be formulated as:

$$\varphi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \quad (2)$$

In Eq. is a time series of a quantity of historical

observations, d is the order of the difference, p and q are the autoregressive model order and the moving average of previous observations, and ε_t is a sequence of independent and identically distributed white noise with zero mean and constant variance. B is the lag operator, and B satisfies the following expression:

$$B^n y_t = y_{t-n} \quad (3)$$

$$\varphi(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p \quad (4)$$

$$\theta(B) = 1 - \theta_1 B - \dots - \theta_q B^q \quad (5)$$

The construction of the ARIMA (p, d, q) model focuses on the selection of the three parameters of (p, d, q). d is the order of differencing, and the purpose of differencing is to make the original series of observations into a smooth time series. In this paper, the Bayesian Information Criterion (BIC) is used to select p and q . The Bayesian Information Criterion gives evidence of a simple approximation of the logarithmic model as follows:

$$BIC = Accuracy(m) - \frac{p}{2} \log N \quad (6)$$

Where p is the number of parameters and N is the number of data points.

The ARIMA model is then built as shown in Figure 7.

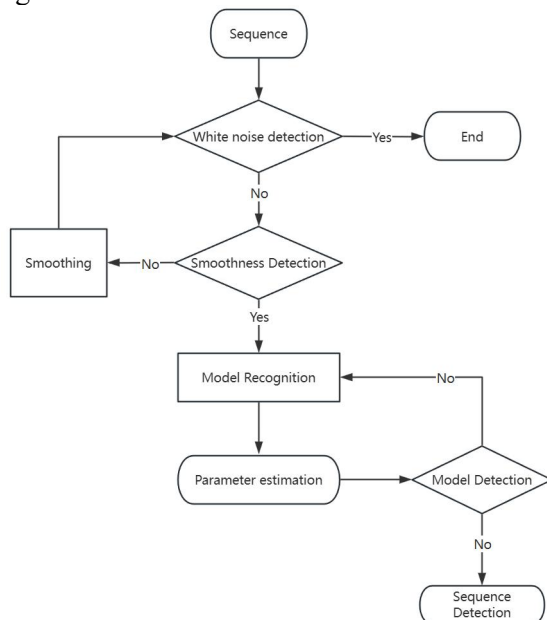


Figure 7. ARIMA Model Building Flowchart
Table 1. Predictions for China's pet industry in the next three years

	2024	2025	2026
Penetration rate (%)	20	17	17
Cats(in 10,000s)	6763	6583	6433
Dog(in 10,000s)	5289	5295	5290

Based on ARIMA model forecasts, Table 1 predicts a decline in both pet ownership penetration and cat numbers, while the dog population remains stable over the next three years.

3. Model and Solution for Problem 2

3.1 Global Pet Industry Development over the Past 5 Years

In recent years, the pet industry in overseas markets, particularly in European countries and the United States, has experienced a period of rapid growth. With the development of the global pet industry, the global pet industry will continue to grow and evolve towards high quality, online, healthy, personalized and sustainable [10].

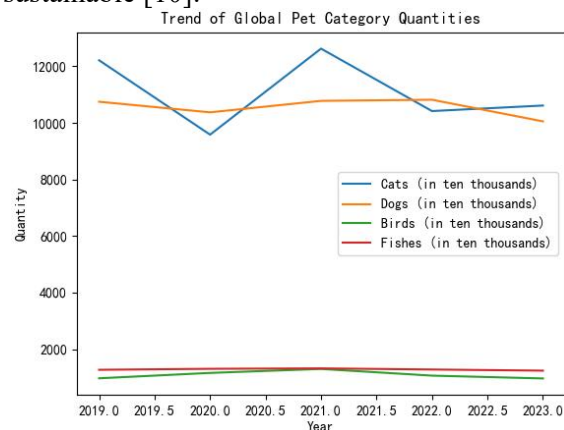


Figure 8. Trend of Global Pet Category Quantities

Figure 8. chart illustrates the trend in the number of different pets from 2019 to 2023. The number of cats is characterised by a fluctuating trend, with a decline followed by an increase and then a period of stability.

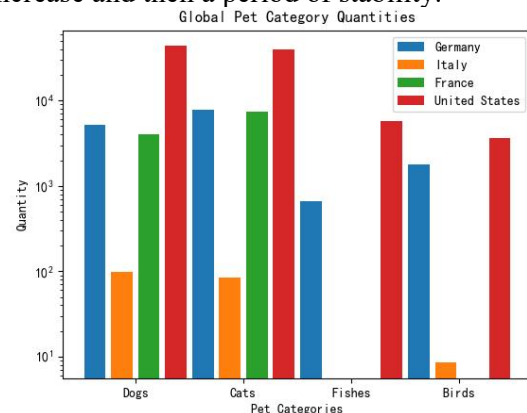


Figure 9. Global Pet Category Quantities

Figure 9. chart presents a comparative analysis of the ownership rates of various types of pets in Germany, Italy, France, and the United States.

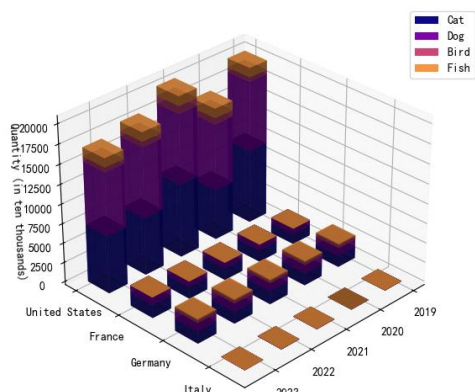


Figure 10. Last 5 Years of Global 3D Stacking by Pet Types

Form Figure 10., the 3D stacked bar chart illustrates the distribution of pet populations across the categories of cats, dogs, birds and fish in the United States, France, Germany and Italy between the years 2019 and 2023.

3.2 Prediction Model: GM (1,1)

3.2.1 Model establishment

A grey prediction model based on food development in the global pet industry.

The Grey Prediction Model is a time series forecasting method that is based on the theory of grey systems.

(1) Modelling principles

Accumulation Generation (AGO): AGO is performed on the raw data X_0 to produce a smoothed series X_1 , with the aim of reducing data fluctuations and highlighting trends.

$$x_1(k) = \sum_{i=1}^k x_0(i), \quad k = 1, 2, \dots, n \quad (7)$$

Differential equation modelling: First order linear differential equation for the cumulative generated sequence X_1

$$\frac{dx_1(t)}{dt} + ax_1(t) = u \quad (8)$$

Solving the model parameters: using ordinary least squares, the parameters a and u were calculated based on historical data, and the complete model was determined.

Prediction of future values: The future cumulative series values are first solved by differential equation and then reduced to the original series values by Inverse Accumulation Generation (IAGO).

$$\hat{x}_1(k+1) = [x_0(1) - \frac{u}{a}]e^{-ak} + \frac{u}{a} \quad (9)$$

$$\hat{x}_1(k+1) = \hat{x}_1(k+1) - \hat{x}_1(k) \quad (10)$$

(2) Prediction formula

Cumulative series prediction formula: formula

Original sequence prediction formula: formula

(3) Methods to get parameters

Construct a cumulative generation sequence: Cumulative generation of the original sequence X_0 to obtain X_1

Construct the data matrix: use the cumulative generation sequence to construct the data matrix B and the target vector Y .

Solve the parameters: Use ordinary least squares to calculate $A = [a, u]^T$, where: $a = A[0]$, $u = A[1]$.

(4) Model validation

Residual analysis: Calculate the residuals between the actual and predicted values and check whether the distribution of residuals is consistent with the model assumptions.

$$\varepsilon(k) = x_0(k) - \hat{x}_0(k) \quad (11)$$

Posterior difference ratio (C value): used to measure the ratio of residual variance to raw data variance. when $C < 0.35$, the model accuracy is level 1; when $0.35 \leq C < 0.5$, the model accuracy is level 2.

Probability of small error (P-value): whether the statistical residual deviation meets the conditions to decide whether the data points are 'small error', the probability of small error P indicates the proportion of 'small error points' to the total number of data points.

3.2.2 Forecast and analysis

Data from global pet food sales 2010-2023.

Model prediction results and testing.

The grey prediction model was used to predict the global pet food sales in the next three years: firstly, I accumulated the historical data, and then defined the data matrix and data vector, and then used the ordinary least squares method to calculate the parameters a and u of the GM(1,1) differential equation, and then established the grey prediction model, and tested the accuracy of the model by solving the a posteriori difference ratios and the probability of a small error, and the model passed the first level of accuracy test. When the model passes the first level accuracy test, it starts to forecast and successfully predicts the global pet food sales in the next three years. Table 2. are the results:

Table 2. Global Pet Food Sales in the Next Three Years (billions of dollars)

	2024	2025	2026
Global pet food sales	133.96	143.95	154.69

4. Model and Solution for Problem 3

4.1 Analyze the Development of China's Pet Food Industry

In recent years, the acceleration of consumption upgrading, capital inflows and overseas mergers and acquisitions have brought unprecedented development opportunities and challenges to China's pet industry.

According to Figure 11, China's pet food production and export value will continue to grow in 2019-2023, indicating a thriving industry and rising international competitiveness.

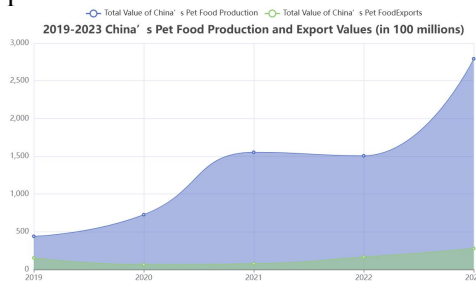


Figure 11. 2019-2023 China's Pet Food Production and Export Values (in 100 Millions)

4.2 Prediction Model 1: Multiple Regression Model

China Pet Food Production Value Forecast

The data comes from China's pet food production and exports and the United Nations' global pet food imports and exports for 2019-2023.

To better predict China's pet food production value, global pet food market demand trends and data related to China's development were analyzed. Correlation analysis was conducted to ensure the independence of the independent variables, and assumptions regarding import/export values and exchange rates were made. Several regression models were constructed: Linear Regression, ElasticNetCV, XGBRegressor, and a Voting Regressor ensemble model. The model with an R^2 value closest to 1 was selected for prediction. Below are the explanations for each model, including formulas where appropriate.

(1) Linear regression model:

Linear regression assumes a linear relationship between the independent variables (X) and the dependent variable (y). The model aims to find the best-fitting line by minimizing the residual sum of squares (RSS). The formula is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon \quad (12)$$

where β_0 is the intercept, β_n are the coefficients,

and ε is the error term. The goal is to estimate the coefficients β that minimize the residuals between the predicted and actual values of y .

(2) ElasticNetCV model:

ElasticNetCV is a regularized regression model that combines L1 (Lasso) and L2 (Ridge) regularization. The objective function for ElasticNet is:

$$\minimize \left(\frac{1}{2n} \sum_{i=1}^n (y_i - X_i \beta + \lambda_1 \|\beta\|_1 + \frac{\lambda_2}{2} \|\beta\|_2^2) \right) \quad (13)$$

Where λ_1 and λ_2 are the regularization parameters, and $\|\beta\|_1$ and $\|\beta\|_2^2$ are the L1 and L2 norms of the coefficients, respectively. ElasticNetCV uses cross-validation to find the best combination of regularization parameters.

(3) XGBRegressor model:

XGBRegressor (Extreme Gradient Boosting Regressor) is an implementation of gradient boosting, where multiple weak models (usually decision trees) are combined in an iterative process to correct the errors of previous models. The objective function for XGBRegressor is:

$$L(\theta) = \sum_{i=1}^n \ell(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (14)$$

where $\ell(y_i, \hat{y}_i)$ is the loss function (usually mean squared error), $\Omega(f_k)$ is the regularization term that penalizes the complexity of the trees, and $\hat{y}_i$ are the predictions made by the ensemble of trees.

(4) Voting Regressor model:

A Voting Regressor is an ensemble method that combines predictions from multiple base models, such as Linear Regression, XGBRegressor, and others. The final prediction is made by averaging the predictions from all the individual models. The formula for a voting regressor is:

$$\hat{y}_{final} = \frac{1}{N} \sum_{i=1}^N \hat{y}_i \quad (15)$$

Where $\hat{y}_i$ is the prediction from the i -th base model, and N is the number of base models used.

In practice, all four models produced R^2 values close to 1, demonstrating their strong predictive performance. The Voting Regressor model was selected for the final output owing to its robustness and capacity to integrate the strengths of all individual models.

In order to predict the total output value of pet food in China in the next three years, a series of

models were used, including LinearRegression, ElasticNetCV, XGBRegressor and VotingRegressor. The data were first subjected to correlation analysis and feature extraction, and then the regression model was fitted with China's pet food import and export value as the feature. To improve the accuracy of the prediction results, a fusion model was constructed. That is, the VotingRegressor model balanced the bias and variance of each model by its integration strategy, and the coefficient of determination of each model was calculated to test the model accuracy, and finally the prediction results of the VotingRegressor model for the total output value of pet food in China in the next three years were chosen as the output results. Table 3 are the results:

Table 3. Total Value of China's Pet Food Production Forecast for the Next Three Years

year	Total Value of China's Pet Food Production
2024	2818.585264
2025	2357.424075
2026	2405.854688

4.3 Prediction Model 2: Liner Regression Model

China Pet Food Export Value Forecast.

The data comes from China's pet food production and exports and the United Nations' global pet food imports and exports for 2019-2023.

Combined with the global pet food market demand trends and China's development, linear regression was chosen as this forecast of China's pet food export value, model reference 4.2(1).

The total value of China's pet food exports in the next three years was predicted using the LinearRegression model: similarly, the linear regression model was fitted with China's imports and exports of pet food as the characteristics, and the regression coefficients were used to test the model accuracy and successfully predict the total value of China's pet food exports in the next three years in Table 4.

Table 4. Total Value of China's Pet Food Exports forecast for the Next Three Years

year	Total Value of China's Pet Food Exports
2024	337.0784014
2025	263.3991324
2026	272.8588674

5. Model and Solution for Problem 4

5.1 Foreign Policy Factors

It is inevitable that China's pet food industry will be influenced by the new foreign economic policies from European countries and the United States. In order to quantitatively analyse this influence, it is necessary to consider a number of different aspects and to utilise the data that has been collected.

5.1.1. Tariff impact

Tariffs are one of the most direct tools used in foreign economic policies. An increase in tariffs can impact both the cost structure and the competitiveness of pet food exports. Tariffs can influence the export price elasticity of demand [11]. Regression analysis, elasticity models, and residual analysis were therefore employed for modeling.

$$\text{Export} = \beta_0 + \beta_1 \times \text{Tariff} + \sigma \times \text{Mat} + \varepsilon \quad (16)$$

where: β_0 is the baseline export value, β_1 represents the elasticity coefficient of exports relative to changes in tariff levels, Tariff is the tariff rate, Mat includes any material or market-related factors affecting exports, ε is the error term.

5.1.2. Exchange rate fluctuations

Exchange rate fluctuations can significantly affect the cost and competitiveness of imports and exports [12]. When the exchange rate fluctuates, it changes the relative price of goods, which can either increase or decrease demand for Chinese pet food products. A simplified model for exchange rate impact is proposed as follows:

$$\text{Export Value} = \beta_0 + \beta_2 \times \text{Exchange Rate} + \sigma_{\text{ex}} \times \text{Export Growth} + \varepsilon \quad (17)$$

where: β_2 captures the relationship between exchange rates and export value, Exchange Rate refers to the currency exchange rate between China and its trading partners, Export Growth measures the growth rate of exports over time.

5.1.3. Trade barriers

Non-tariff barriers such as quotas, licensing requirements or quality control regulations can limit market access or increase costs, creating additional challenges for Chinese pet food exporters [13]. Potential models of the impact of trade barriers could be as follows:

$$\text{Export} = \beta_0 + \beta_3 \times \text{Trade Barriers} + \sigma_{\text{tb}} \times \text{Compliance Costs} + \varepsilon \quad (18)$$

where: β_3 reflects the sensitivity of exports to the imposition of trade barriers, Trade Barriers includes measures like product quotas and

licensing, Compliance Costs measures the financial burden of adhering to foreign regulations.

5.1.4. Infrastructure factors

Inadequate infrastructure can lead to delays and higher costs [14], negatively impacting the pet food export market. The impact of infrastructure can be modeled as follows:

$$\text{Export} = \beta_0 + \beta_4 \times \text{Infrastructure Index} + \sigma_{\text{infrastructure}} + \text{Logistics Costs} + \varepsilon \quad (19)$$

where: β_3 measures the influence of infrastructure quality on export performance, Infrastructure Index is a composite measure of transportation and logistics infrastructure, Logistics Costs quantify the cost of moving goods across borders.

5.2 Prediction Model: Custom Function Model

To quantitatively analyze the impact of new foreign economic policies from Europe and the United States on China's pet food industry, the predicted total value of China's pet food exports from Question 3 was applied. Tariff policies, exchange rate fluctuations, trade barriers, and infrastructure conditions were quantified as tariff rates, exchange rates, a trade barrier index, and an infrastructure index, respectively. The initial sensitivity of export value to each policy index was established, and assumptions were made regarding changes in each policy indicator over the following three years. Finally, function realisation is carried out for each policy indicator, thus constructing a function prediction model for the total value of China's pet food exports after being affected by the economic policies of Europe and the United States. Table 5. are the results.

Table 5. Total Value of China's Pet Food Exports Forecast for the Next 3 Years (Influenced by New Foreign Trade Policies)

year	Total Value of China's Pet Food Exports (Influenced by new foreign trade policies)
2024	320
2025	252.19
2026	249.52

5.3 Possible Strategies for Sustainable Development

In response to the foreign economic policies of the United States and European countries, the Chinese pet food industry must adopt proactive strategies to ensure sustainable growth. Here are some strategic recommendations:

5.3.1 Diversification of export markets

To reduce the risk of heavy dependence on a small number of countries, China should diversify its export markets. By targeting emerging economies with growing demand for pet food such as Southeast Asia and Africa.

5.3.2 Invest in research and development (R&D)
Innovation in product quality, packaging and production efficiency, investment in R&D will enable companies to provide quality products that meet international standards, thereby overcoming trade barriers.

5.3.3 Improving logistics and supply chain infrastructure

Strengthening domestic infrastructure and improving logistics capabilities will reduce costs associated with international trade. This includes upgrading ports, transport networks and warehousing facilities to streamline supply chains and minimise delays.

5.3.4 Establish strategic partnerships

Partnering with foreign distributors and pet food companies in target markets can help Chinese manufacturers bypass trade barriers. These partnerships can also promote local production or joint ventures, making companies less vulnerable to tariffs and import regulations.

5.3.5 Negotiating government trade agreements
The Chinese government should strive to negotiate favorable trade agreements with its major trading partners to reduce tariff and non-tariff barriers.

6. Sensitivity Analysis and Error Analysis

6.1 Sensitivity Analysis

A univariate sensitivity analysis was employed in the evaluation of the XGBRegressor Nonlinear Model Predictive Control, with the investigation focusing on the sensitivity of the model state to alterations in the exchange rate as the independent variable. The range of exchange rate changes was set manually, and the mean change in the output was then calculated.

Sensitivity Analysis for Feature exchange rate

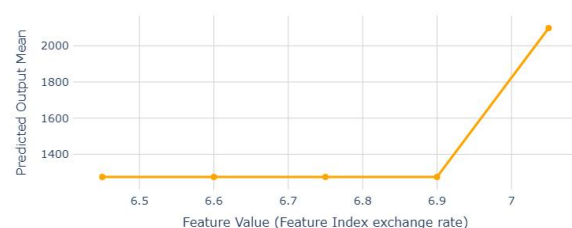


Figure 12. Sensitivity Analysis for Feature Exchange Rate

Figure 12. illustrates that when the exchange rate surpasses 6.9, the output of the model, namely the mean output value of pet food in China, is subject to a more pronounced impact, nearly exponential in nature. This suggests that the output of the model is highly sensitive to this aspect of the exchange rate.

6.2 Error Analysis

All tests of the model were conducted subsequent to the research process.

During testing of the ARIMA model, an ACF plot was generated, as illustrated below Figure 13.

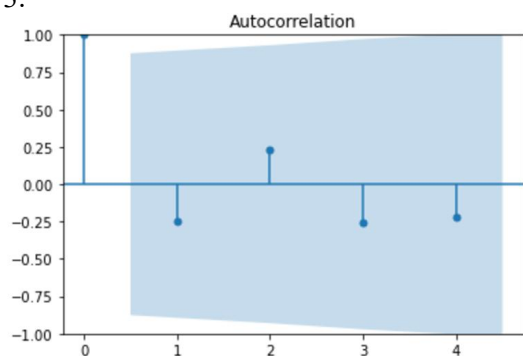


Figure 13. ACF

All the points fall within the confidence interval, with the exception of the first one, which indicates that our model is not significantly affected by white noise and has effectively captured the significant patterns in the time series data.

During the assessment of the grey prediction model, the a posteriori difference ratio and the small error probability were resolved. The outcomes demonstrated that the a posteriori difference ratio of the model is, in fact, less than 0.35, and that the small error probability is, in fact, greater than 0.95. This signifies that our model attains the first degree of accuracy.

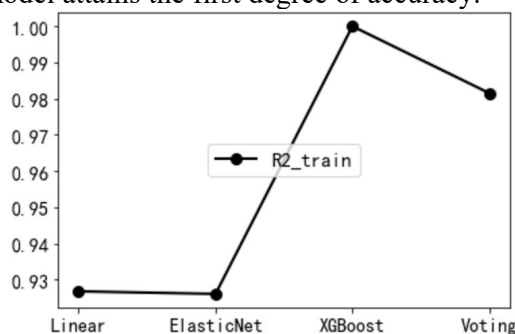


Figure 14. Regression Coefficients of the Models

During testing of the composite regression model, the regression coefficients for each model were solved. As illustrated in Figure 14,

the models demonstrated excellent performance.

7. Model Evaluation and Further Discussion

7.1 ARIMA-Time Series Model

The utilization of autoregressive techniques to anticipate forthcoming values by reference to historical data is an efficacious approach for univariate time series exhibiting trends and seasonality. However, this approach may not be optimal for the capture of multivariate relationships or when the amount of data is limited. To enhance the efficacy of this approach, it is recommended to consider the application of multivariate ARIMA models (e.g., VAR models) to multivariate data or the integration of these with other models, such as LSTM, in order to facilitate the capture of intricate relationships and long-term dependencies within the data.

7.2 Grey Prediction Model

The model demonstrates proficiency in the processing of limited data sets and incomplete information, as well as the identification of trends through the utilization of differential equations. However, its efficacy is diminished when confronted with extensive data sets or intricate relationships. To enhance its effectiveness, it would be beneficial to combine it with other machine learning models (e.g., Random Forest or XGBoost) or to utilize optimization algorithms to refine the parameters of the grey model, thereby improving its accuracy.

7.3 Multiple Regression Model

The integration of multiple regression techniques, including linear regression, elastic net, XGBoost, and voting regressor, enhances the prediction accuracy and robustness when dealing with linear and non-linear model predictive control. This is achieved by combining the strengths of each model. Although this composite model offers flexibility and high performance, it is more computationally complex and, particularly in the case of tree models such as XGBoost, less interpretable. To enhance this further the outputs of the model can be interpreted through the use of interpretability enhancement techniques, such as SHAP or LIME. Additionally, weighted voting mechanisms can be employed to reduce the computational

complexity of the model and improve its stability.

7.4 Custom Function Prediction Model

The model is a streamlined and effective instrument for rapidly anticipating the immediate impact of tariff policies, fluctuations in exchange rates, trade restrictions, and infrastructure on the value of China's pet food exports. However, its principal drawback is that it simplifies intricate economic relationships in an overly simplistic manner. To enhance the model's predictive precision and versatility, the incorporation of multivariate, time series, or machine learning methodologies, coupled with a more comprehensive array of economic policy variables, can facilitate a closer alignment with the intricate nuances of the actual economic landscape. Furthermore, the model's utility as a decision-support tool can be enhanced by improving its interpretability.

8. Conclusion

8.1 For Question 1

China's pet industry has grown significantly and diversified over the past five years. The ARIMA model predicts that the number of dogs and cats will grow steadily from 2019 to 2023, the penetration rate of pet-owning households and the number of pet cats will show a decreasing trend in the next three years, and the number of pet dogs will be relatively stable without any significant fluctuations.

8.2 For Question 2

The pet food industry in Europe and the United States has been growing rapidly in recent years, and the GM (1,1) model in the grey forecasting model is used to predict the global pet food sales, which will show a growth trend in the next three years, but face the impacts and challenges of many factors.

8.3 For Question 3

China's pet food production value and export value will continue to grow from 2019 to 2023 but the gap is widening. The multi-model forecast predicts that the production value will first decrease and then slightly increase in the next three years, and the linear regression model of export value shows that it will first decrease and then slightly recover.

8.4 For Question 4

A custom function model is adopted to quantify the policy factors and combine with the previous forecasts to construct a model, which predicts that China's pet food export value will first decrease and then slightly increase in the next three years, and puts forward the strategies of export diversification, investment in R&D, improvement of infrastructure, and establishment of strategic partners.

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