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A Multi-Model Predictive Analysis of China's Pet Industry Development: Market Trends, Global Demand, and Strategic Responses to Foreign Economic Policies

Shen Gaojiayue*

Mathematics and Applied Mathematics Program at the Jinan University–University of Birmingham Joint College, Jinan University, Guangzhou, 511400, China

**Corresponding author: Shen Gaojiayue.*

Abstract

This study aims to analyze the development trajectories of China’s pet industry and its pet food sector, forecast future market demands, and quantitatively assess the impact of foreign economic policies to formulate sustainable development strategies. By integrating multivariate linear regression, nonlinear regression, and polynomial linear regression models within a weighted framework optimized via a particle swarm optimization algorithm, we first evaluate China’s pet industry development based on pet populations and market sizes, predicting that by 2026, the number of pet cats and dogs in China will reach approximately 93.95 million and 42.66 million, respectively. To forecast global pet food demand, we apply cubic spline interpolation to supplement missing international data and construct a similar weighted model incorporating per capita GDP, projecting pet population trends across seven major markets. Focusing on China’s pet food sector, we develop a multiple linear regression model to predict production value, alongside a hybrid weighted model combining support vector regression (SVR) and random forest regression to forecast export values, yielding expected production and export values of 5,993.98 and 46.79 (in 100 million USD) by 2026, respectively. All models are validated using mean absolute percentage error (MAPE), root mean square error (RMSE), and comparisons with auto regressive integrated moving average (ARIMA) models. To quantify the influence of foreign tariff policies, we conduct correlation analysis revealing a coefficient of up to 0.87 between exchange rates and imports, then employ an SVR model to predict that China’s pet food exports would reach 44 (100 million USD) by 2028 under policy shifts. An independent samples t-test indicates a significant difference in China’s pet food export values before and after 2021. Consequently, we propose feasible strategies for the sustainable development of China’s pet food industry, including market diversification and supply chain optimization to mitigate external policy risks.

Keywords

multivariate linear regression model, nonlinear regression model, polynomial regression model, support vector regression (SVR), random forest regression model, t-test

1. Introduction

1.1 Background

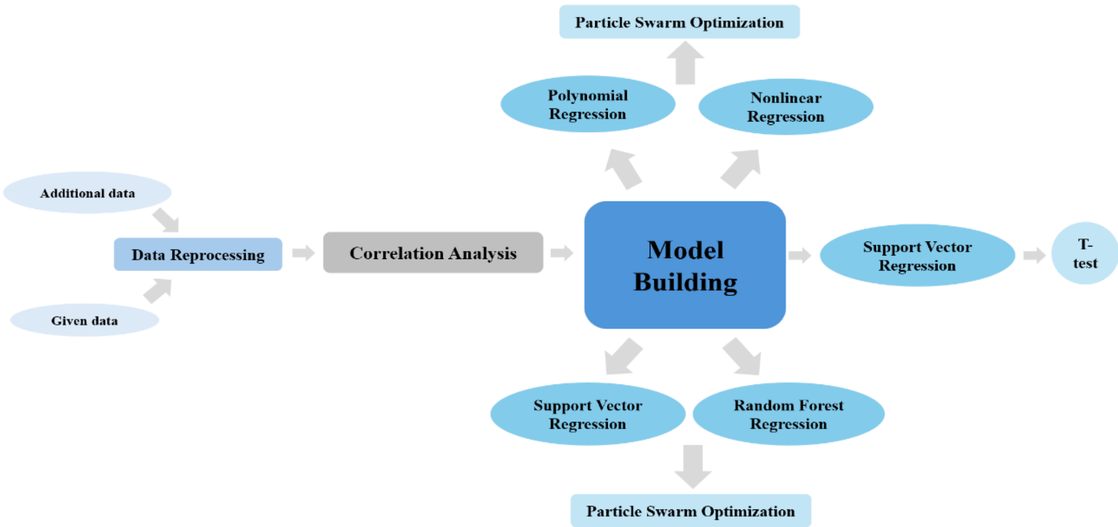
The global pet industry has grown rapidly due to rising incomes and changing consumer attitudes toward pet companionship. In China, the modern pet industry emerged in the early 1990s and has since expanded significantly, covering pet food, medical care, supplies, and services. However, accurate forecasting and strategic planning are challenged by data fragmentation, demand complexity, and vulnerability to foreign economic policies such as tariffs.

1.2 Our Work

This study aims to analyze China's pet industry development, forecast its pet populations and pet food production and export, and quantitatively assess the impact of external policies. Using data from 2019–2023 on pet numbers in China and overseas (U.S., France, Germany), plus China's pet food production and export values, we selected different indicators from data given and collected for quantification and analysis.

First, we build a weighted prediction model (combining multivariate linear, nonlinear, and polynomial regression) optimized by particle swarm optimization (PSO) to forecast China's pet cat and dog populations. Second, we apply cubic spline interpolation and a similar weighting model to predict global pet food demand. Third, we use multiple linear regression and a hybrid SVR-random forest model to forecast China's pet food production and export values. Fourth, we analyze the impact of foreign tariff policies via correlation analysis, SVR-based export forecasting, and an independent samples t-test. All models are validated using MAPE, RMSE, and comparisons with ARIMA. The overview of our work is shown in Figure 1.

Figure 1: Overview of Our Work



2. Model Assumptions and Data Source

2.1 Assumptions

1) Assuming that the data acquired through the search possesses a certain level of credibility and rationality.
2) Assuming the GDP per capita growth rate of 4.5%.
3) Assuming that the exchange rate of the RMB against the US dollar decreases by an average of 2% per year over the next three years.
4) Assuming that the proportion of food exports increases by 0.01 per year after 2024.
5) Assuming that U.S. pet food imports increase by 0.03 percent per year.

2.2 Data Source

The data used in this study are mainly from the National Bureau of Statistics of China, Guanyan Report Network, China Business Intelligence Network, and Huajing Industry Research Institute, covering the period 2019–2023. Detailed data types and corresponding sources are listed in Table 1below.

Table 1: Data Source

Data	Source
Per Capita GDP	National Bureau of Statistics
Disposable Income	
Urbanization Rate	
Population Over 65 (millions)	
Pet Food Market Scale (100 million)	Guanyan Report Network
Pet Medical Industry Market Scale (100 millions)	China Business Intelligence Network
Propotion of Pet E-commerce Chanels	Huajing Industry Research Institute

3. Task 1: Development quantization and prediction model

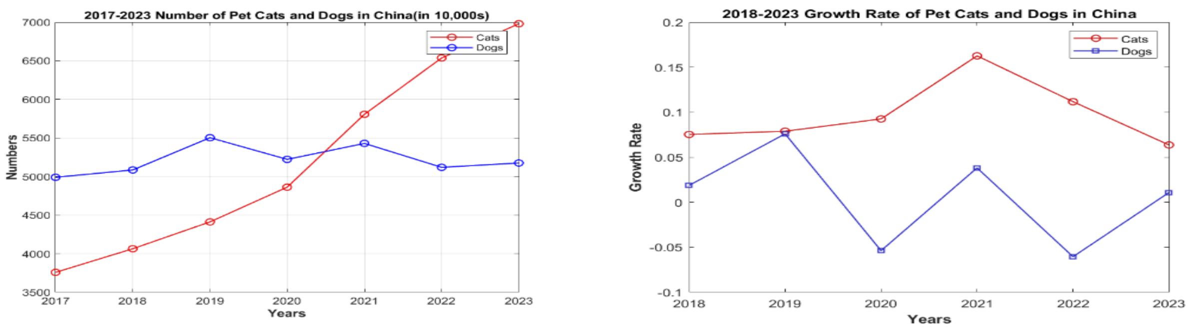
3.1 Data Description

Based on the pet type, analyze the development of the pet industry in China over the past five years, dissect the factors in the development of the pet industry, and then establish a corresponding mathematical model to predict the growth of our pet industry over the next three years.

3.1.1 Data Collection and Visualization

We utilize known data to reflect the development of the pet industry in China over the past five years through the changes in pet numbers in order to better understand the trends in the data, the key variables of the pet industry were visualized through two sub figures below.

Figure 2: The Development of China's Pet Industry over the Past Five Year



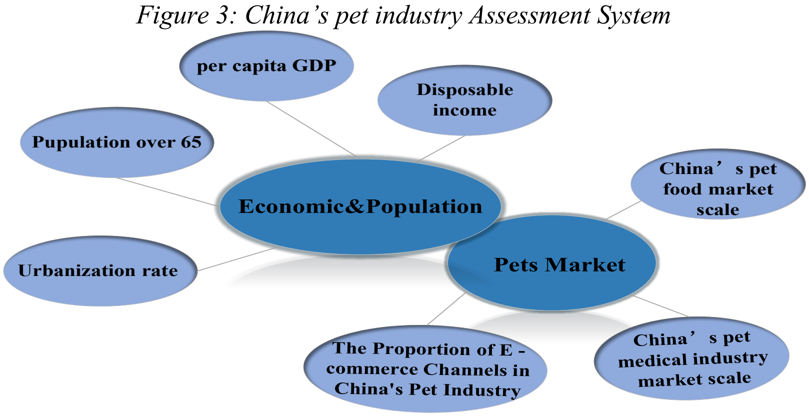
As shown in the figure, Changes in the number of pets in China can be observed, and it can be noted that there are significant fluctuations in the number of dogs, especially between 2020 and 2021, when there is a more significant decline in the number of dogs. This fluctuation can be attributed to a number of factors, the most prominent of which may be the impact of the epidemic, which has changed the lifestyles of many families, coupled with the relatively high cost of dog ownership, compared to the upward trend in the number of cats, which may be attributed to the fact that cats are relatively easier to care for and rely less on daily travel and outdoor activities.

3.2 Analyze the Influencing Factors

3.2.1 Influencing Factors and Index Setting

To analyze the factors in the development of China's pet industry over the past five years, we have developed a China's pet industry assessment system which is consisting of two important aspects: Economic&Population and Pets Market. Each first-level indicator is divided into many second-level indicators. As shown in Figure 3 below.

Figure 3: China's pet industry Assessment System



1) **Economic&Population:** Economic&Population refer to the fact that in the pet industry, the economic power of consumers directly affects how much they spend on pet-related products and services. And the size of the population largely determines the potential market size of the pet industry. In this aspect, we have selected per capita GDP, Disposable income, Population over 65 and Urbanization rate as secondary indicators.

2) **Pets Market:** Pets Market refers to a comprehensive area of trading goods and services around pets. In this regard, we have selected China's pet food market scale, The Proportion of E-commerce Channels in China's Pet Industry and China's pet medical industry market scale as secondary indicators.

Then, we carried out data visualization processing based on the known data. The results are shown in the following figure.

Figure 4: Influencing Factors

(a) Economy&Population (b) Pet Market

3.2.2 Data Dimensionless Process

Dimensionalization refers to the process of removing the dimensionality of different indicators, which makes them incomparable due to the different units of measurement. Therefore, it is necessary to normalize the data first in order to eliminate the dimensional influence. In order to conduct an in-depth analysis of the factors influencing the development of China's pet industry, we not only analyzed the number of pets but also studied multiple relevant indicators such as those related to the economy, population, and the pet market. Through principal component analysis (PCA), t-SNE dimensionality reduction, and correlation analysis, the main indicators affecting the development of China's pet industry were discussed.

Before performing PCA and t-SNE dimensionality reduction, the data was standardized using the Z-score method to eliminate the impact brought by the different measurement units of various indicators. The standardized data is referred to as data_standardized.

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

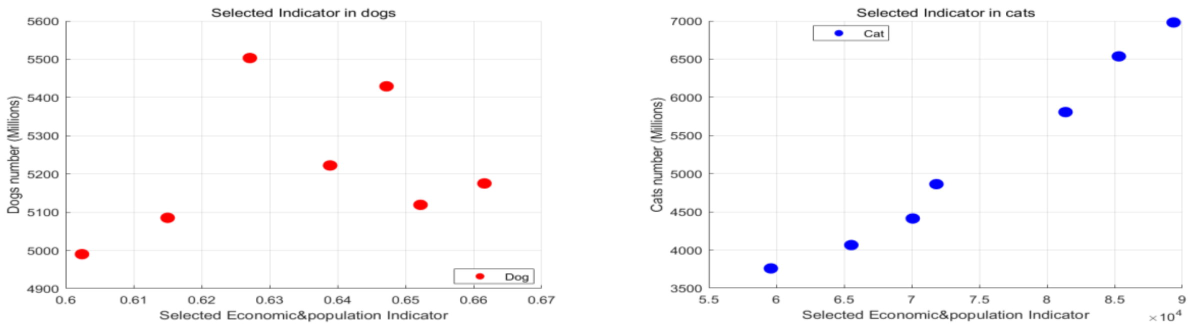
Z represents the standardized data, X stands for the original data, μ is the mean value, and σ is the standard deviation.

3.2.3 Correlation Analysis

(1) Economic&Population Influences

After calculating the correlation coefficients, the indicators with the strongest correlations for cats and dogs were selected as substitute indicators for the economic and population categories. The following two sub figures are scatter plots of dogs and cats respectively with the indicators having the strongest correlations.

Figure 5: Selected Indicator in dogs and cats



As is seen from the figure, the number of pet cats has a stronger correlation with the economic demographic category of influences, and pet dogs have a weaker and more fluctuating correlation with the economic demographic category of influences.

Table 2: Correlation coefficient of cats and dogs

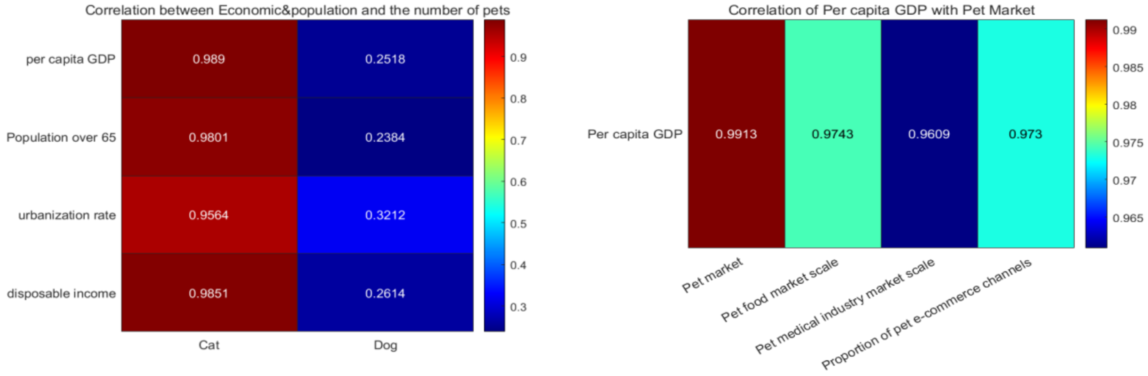
Index	Per capita GDP	Population over 65	Urbanization rate	Disposable income
Correlation coefficient	0.9890	0.9801	0.9564	0.9851
Index	Per capita GDP	Population over 65	Urbanization rate	Disposable income
Correlation coefficient	0.2518	0.2384	0.3212	0.2614

From Table 2, the correlation coefficient between cats and economic and demographic factors is above 0.9, indicating a high and positive correlation, with an increase in GDP per capita, the number of people over 65 years of age, the urbanization rate and the disposable income of the population, the number of pet cats also increases.

The correlation coefficient between dogs and economic and demographic factors is below 0.4, indicating a low correlation, and the number of pet dogs is less associated with GDP per capita, the number of people over 65 years of age, the urbanization rate and disposable income of residents.

In order to see more clearly the differences in the correlation coefficients of the Economic&Population category of influences with cats and dogs, we created a heat map comparison of the correlation coefficients. At the same time, we analyzed the correlation coefficient between GDP per capita in the Economic&Population factors and the market size of pet-related business in the whole city, and made a chart to provide a data base for the subsequent correlation analysis.

Figure 6: Visualization of correlation coefficients



(2) Pets Market Influences

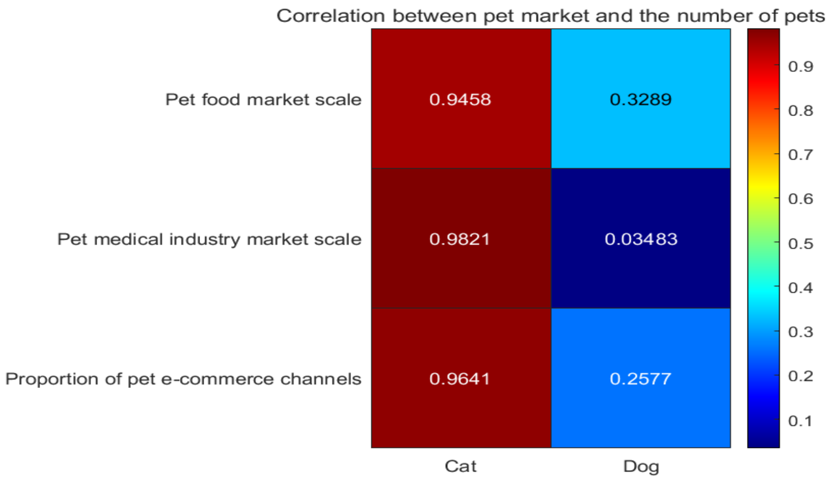
Table 3: Correlation coefficient of cats and dogs

Index	Pet food market scale	Pet medical industry market scale	Proportion of pet e-commerce channels
Correlation coefficient	0.9458	0.9821	0.9641
Index	Pet food market scale	Pet medical industry market scale	Proportion of pet e-commerce channels
Correlation coefficient	0.3289	0.0348	0.2577

From Table 3, the correlation coefficient between cats and Economic&Population factors is above 0.9, indicating a high correlation and positive correlation. With the increase in the market size of China's pet food market, the market size of China's pet healthcare industry, and the share of e-commerce channels in China's pet industry, the number of pet cats has also increased.

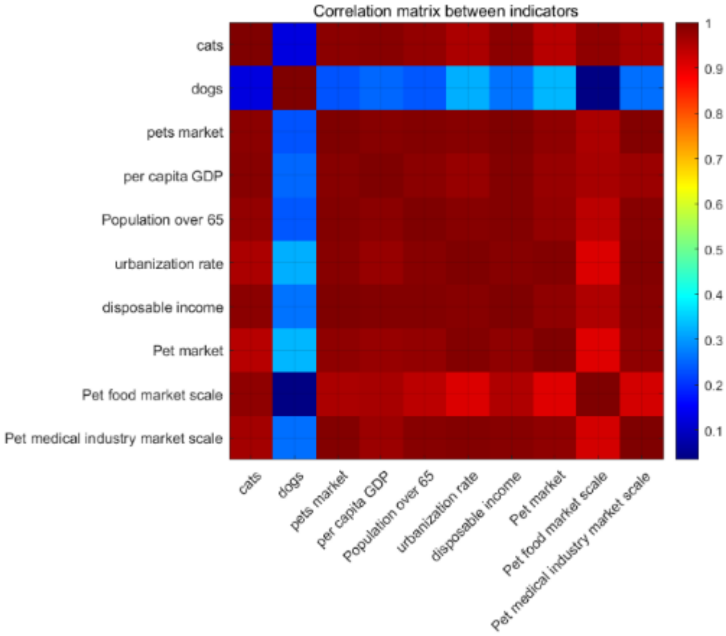
The correlation coefficient between dogs and Economic&Population factors is below 0.4, indicating a low correlation, and the number of pet dogs is associated with the China's pet food market size, China's pet medical industry market size, China's pet industry E-commerce channel share of the correlation is small.

Figure 7: Correlation between pet market and the number of pets



As is seen from the above figure, the number of pet cats has a stronger correlation with the pet market category of influences, and pet dogs have a weaker and more volatile correlation with the pet market category of influences.

Figure 8: Correlation between indicators



We produced a heat map of the correlation analysis between all the influencing factor indicators in the economic-demographic category and the pet market category, from which we can see that pet cats are more strongly correlated with the above indicators

3.3 Forecast the Future Development

3.3.1 Model Building

Based on the above analysis, our forecast targets the number of cats, the number of dogs, and the size of the pet-related business market in the next three years; the forecasts are for the next three years for GDP, food, and medical care. And we construct three prediction models: Polynomial Regression [5]. Nonlinear Regression, and Linear Regression [3]. For the purpose of improving the accuracy of the prediction, the prediction results of the three models are weighted and combined, and the weights are derived by Particle Swarm Optimization Algorithm [4]. Ultimately, we perform an error analysis on the weighted prediction model: residuals comparison.

First, to forecast GDP per capita for the next three years, we utilize GDP per capita from 2017-2023 to derive a growth rate of 0.045, which is used to forecast GDP per capita for the next three years. We then merge historical and future (2017-2026) data to make projections.

- Linear Regression

Constructing a Linear Regression Model with correlation analysis of influential factors shows that the correlation coefficient of GDP per capita is closest to 1. Then GDP per capita is used as an input characteristic to predict the number of cats and dogs in the next three years.

$$\hat{y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{2}$$

X_1 and X_2 refer to the population growth rate and per capita GDP respectively, and $\beta_0, \beta_1, \beta_2$ is the regression coefficient of the model.

- Polynomial Regression

Construct a Polynomial Regression Model [5] to predict the number of cats and dogs in the next three years using a Second-Order Polynomial Regression Model.

$$\hat{y} = a_2 t^2 + a_1 t + a_0 \tag{3}$$

- Nonlinear Regression

Constructing a Nonlinear Regression Model to predict the number of cats and dogs over the next three years using Exponential Modeling.

$$\hat{y} = ae^{bt} \tag{4}$$

a and b are the fitting parameters, t is particular year.

- Particle Swarm Optimization Algorithm

Construct the Weighted Prediction Model, in order to improve the accuracy of the prediction, the prediction results of the three models are weighted and combined, and the weights are derived through the Particle Swarm Optimization Algorithm, and initially, it is assumed that the weights of the three models are the same, which are all $\frac{1}{3}$.

We make separate predictions of the future cat population. The Weighted Prediction Model is of the form:

$$y_{weighted} = w_1 y_{regression} + w_2 y_{poly} + w_3 y_{nonlincar} \tag{5}$$

Our objective is to find the optimal weights w_1, w_2, w_3, minimizing the error between the weighted prediction $y_{weighted}$ and the real value y_{true}. The weights need to satisfy the following constraints:

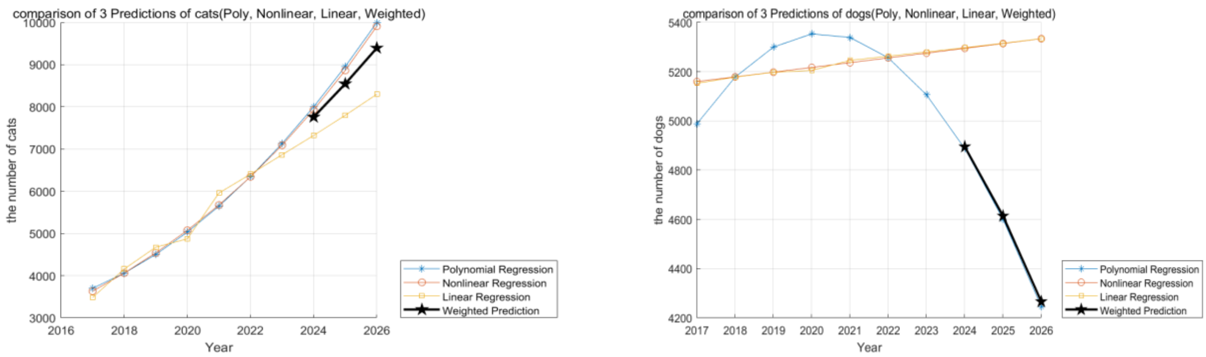
$$w_1 + w_2 + w_3 = 1, w_1, w_2, w_3 \geq 0 \tag{6}$$

3.3.2 Projected Results

Comparing the visualization results of Linear Regression Model, Second-Order Polynomial Regression Model, Nonlinear Regression Model and Weighted Prediction Model.

- Results of cats&dogs population projections

Figure 9: Comparison of 3 Predictions



(a) cats (b) dogs

The datas are shown in Table 4 and Table 5:

Table 4: Weighting results of cats&dogs

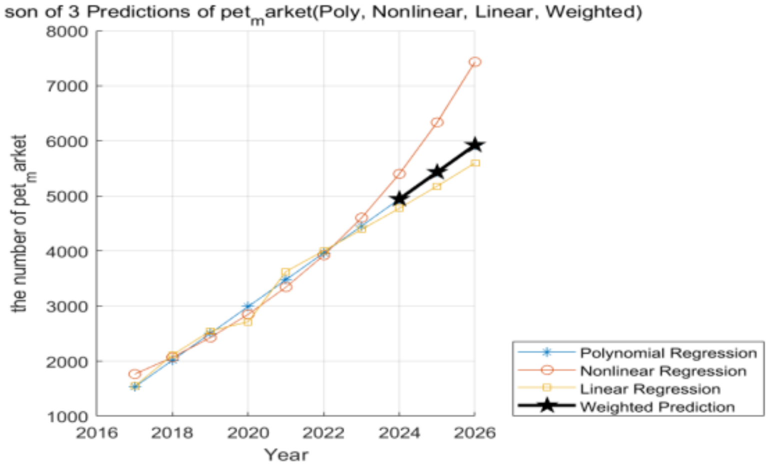
weights	w1	w2	w3
Cats	0.355378325740675	0.644621654128716	0.000000020130609
Dogs	0.018249152837698	0.981750847123097	0.000000000039205

Table 5: Predicted results of cats&dogs

Year	2024	2025	2026
Cats	7760.19	8546.15	9394.83
Dogs	4895.05	4613.9	4265.93

- Results of Pet Related Business Market Size projections

Figure 10: Comparison of 3 Predictions of pet market



The datas are shown in Table 6 and Table 7:

Table 6: Weighting results of pet market

w1	w2	w3
0.002296761327422	0.997703214219880	0.000000024452698

Table 7: Predicted results of pet market

Year	2024	2025	2026
Pets market(billions)	4944.33	5433.98	5924.3

4. Task 2: Global Demand for Pet Food

4.1 Analyze the Development

Based on the data given and collected by the team, analyze the development of global pet industry, and build a suitable mathematical model to anticipate global demand for pet food over the next three years.

To forecasts the global demand for pet food over the next three years by means of a weighted combination,it is solved on the basis of the Multiple Linear Regression, Polynomial Regression, and Nonlinear Regression Models developed in Task 1.

4.1.1 Data Pre-processing and Visualization

First, the necessary processing of the data is required to supplement the missing values of the initially collected data. Since some of the indicators can only be collected on the website, the data given on the website are not available on a yearly basis. In order to facilitate the subsequent calculations, we used the cubic spline interpolation method to supplement the data. The basic idea of cubic spline interpolation is to approximate the data within a small interval of a segment with low degree polynomials and to use the articulation condition at the junction of these polynomials to ensure the smoothness of the whole curve. This treatment can better reflect the trend of each indicator between 2019 and 2023 and provide a more reliable data basis for subsequent analysis and forecasting.

Then we utilize the code to plot the number of cats and dogs, the relationship between pet food expenditure and the total number of pets, the scatter relationship between GDP per capita and pet food expenditure, and the trends in the export volume index and the food production index, visualized as follows:

Figure 11: Visualization Result1

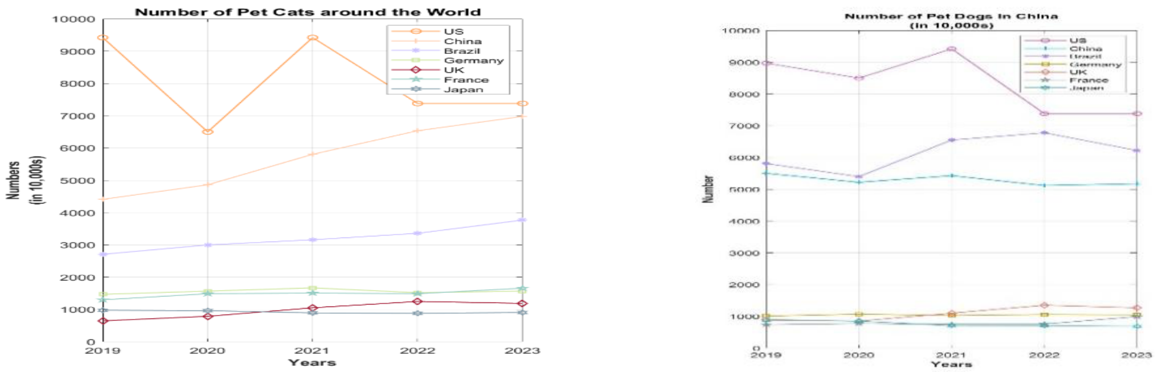
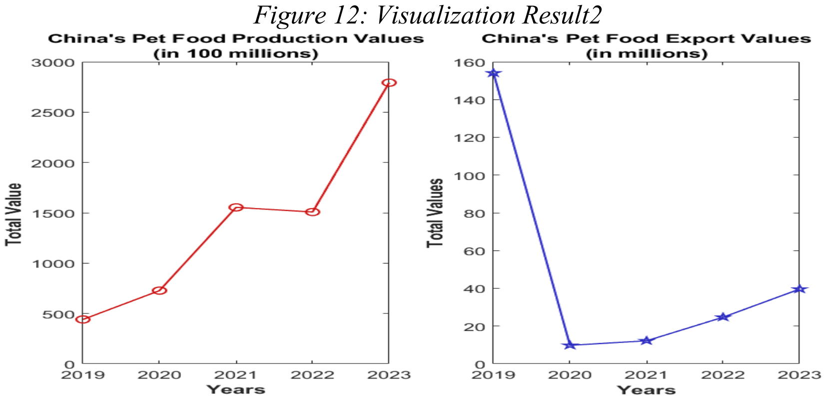


Figure 12: Visualization Result2

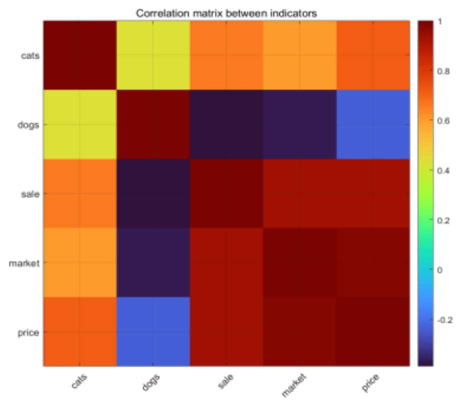


These graphs reveal a strong correlation between pet populations and food expenditures, and reflect the impact of economic factors on the pet market.

4.1.2 Correlation Analysis

The calculation of Pearson's correlation coefficients enabled the quantification of the relationship between each factor and pet food expenditure. We calculated and output a matrix of correlation coefficients between the variables, revealing the following major influences. There is a high positive correlation between pet population, pet food expenditure, pet food sales, pet food market size, and pet food market price.

Figure 13: Correlation matrix between indicators



The results of the correlation analysis provided the basis for further modeling, enabling the selection of key variables most likely to influence future trends. As is known from the figure, the demand for pet food can be reflected by indicators such as the number of pets, pet food expenditure, pet food sales, pet food market size; pet food market price, etc.

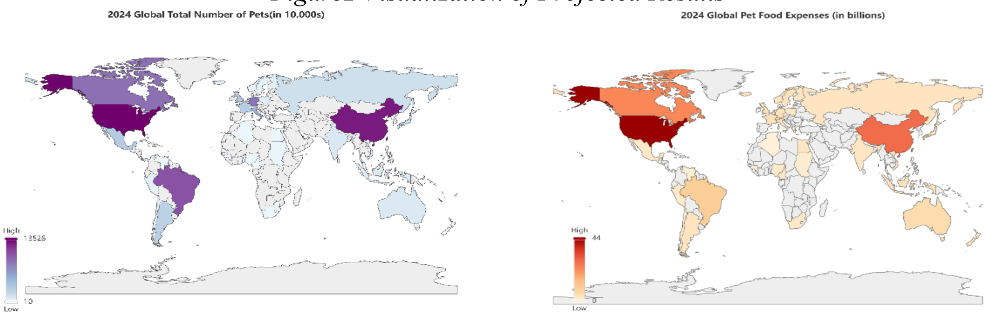
4.2 Projected Results

Globally, through the data collection and analysis, we choose the top seven countries in terms of pet population as our representatives, and consider the influence of GDP, and use the model built in Q1 to predict the number of pet cats and dogs in these seven countries in the next three years (China's prediction result is in Q1), reflecting the global demand for pet food in the next three years. To reflect the reliability of the forecast results, we also forecast pet food spending in the US, Germany and France over the next three years. The results of the projections are shown below:

Table 8: Forecast Results

Country	Index	2024	2025	2026
The USA	Cats	7496.29	7612.64	7853.66
	Dogs	6030	4590	2861.43
	Food	43.9	45.6	47.3858
Germany	Cats	7496.29	7612.64	7853.66
	Dogs	1030	1002.01	964.009
	Food	3.60237	3.80506	4.00867
France	Cats	1666.6	1702.31	1727.81
	Dogs	1145.63	1392.18	1695.26
	Food	4.00229	4.20503	4.40869
Brazil	Cats	4079.6	4493.36	4886.19
	Dogs	6306.53	6046.68	5659.78
The UK	Cats	1230.85	1171.96	1053.47
	Dogs	1435.84	1536.04	1631.75
Japan	Cats	924.435	967.551	1029.02
	Dogs	681.32	703.999	748.465

Figure2 Visualization of Projected Results



This shows that the global demand for pet food is on the rise for the next three years. Of these, demand varies by region, with the U.S. and China accounting for the largest share of demand for pet food.

5. Task 3: Multiple Linear Regression Model

5.1 Analyze the Development

Based on the demand trend in the global pet food market and the development in China, analyze the growth of the pet food industry in China, and forecast the production and export of pet food in China over the next three years (regardless of changes in economic policies).

5.1.1 Data Pre-processing and Visualization

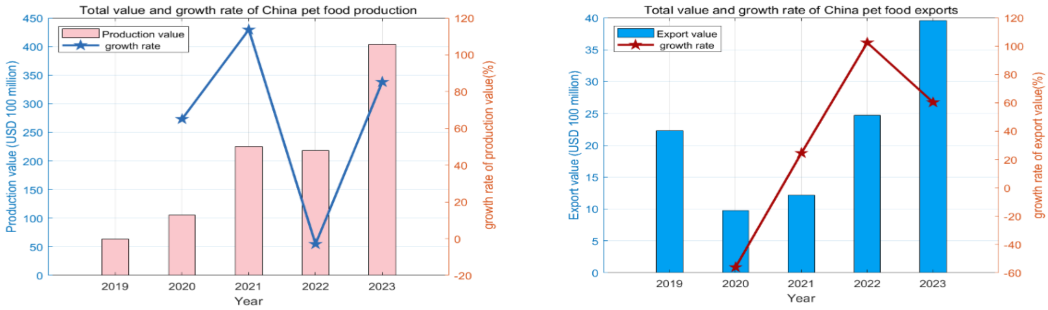
First, we need to dimensionless the data in Table 9, harmonize the units, and convert the units of GDP and total exports to US dollars. Here, we assume that the exchange rate between RMB and USD is 0.144806:1.

Table 9: 2019-2023 China's Pet Food Production and Export Values (in 100 millions)

Values/Years	2023	2022	2021	2020	2019
Total Value of China's Pet Food Production	2793 (CNY)	1508 (CNY)	1554 (CNY)	727.3 (CNY)	440.7 (CNY)
Total Value of China's Pet Food Exports	39.6 (USD)	24.7 (USD)	12.2 (USD)	9.8 (USD)	154.1 (USD)

In order to make the known data more intuitive for us to analyze the development, we visualized the total value and growth rate of China pet food production and exports shown as below:

Figure 15: Total value and growth rate



(a) China pet food production (b) China pet food exports

As can be seen in Figure 15(a), the total value of China pet food production shows a gradual upward trend at a high rate of growth, which is a sign that China's pet food production volume is steadily realizing positive development under the influence of policy and market demand. It's worth noticing that the growth rate of pet food production has experienced a certain decrease, the essential reason for this may be due to the full liberalization policy in 2022, which somehow affects productivity to a certain extent.

Meanwhile, from Figure 15(b), China's pet food exports also shows an steady uptrend. Based on the actual situation, it is not difficult to see that after the blow of the epidemic in 2019, the production volume and market share of China's pet food industry are increasing year by year and continue to develop at a high rate, in 2022, the export values even exceeding the pre-epidemic period.

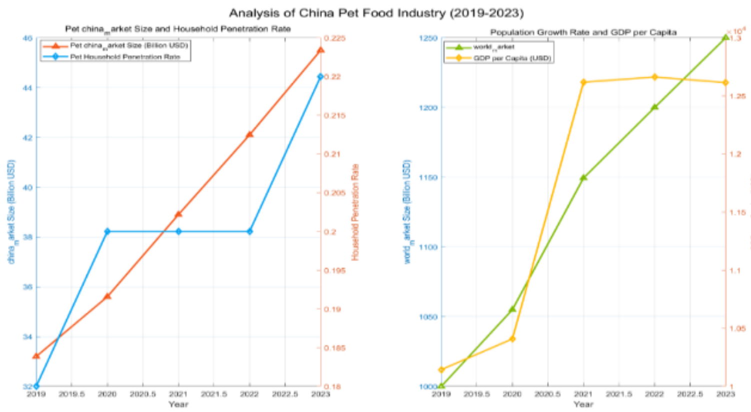
5.2 Model Preparation

5.2.1 Influencing Factors and Index Setting

In order to project as accurately as possible the production and export of China's pet food industry in next three years, we have collected a range of relevant factors and their data for 2019-2023 in Figure 16.

Each model for the prediction of production and export has different factors that need to be taken account, so our first work is to select factors which are highly correlated for the two models.

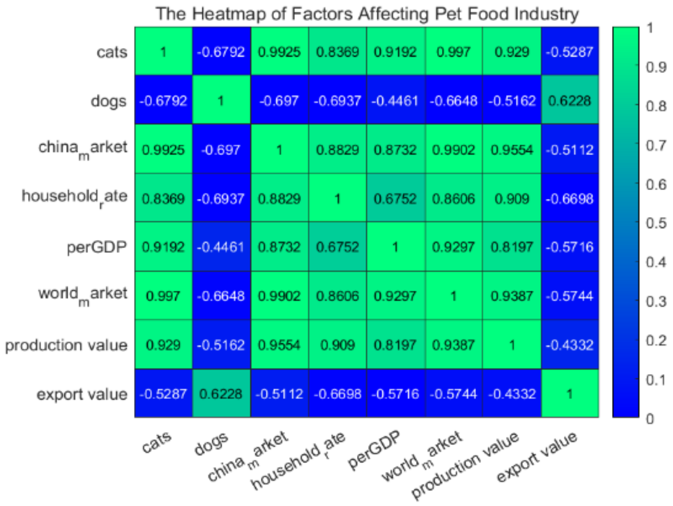
Figure 16: Analysis of China Pet Food Industry (2019-2023)



5.2.2 Correlation Analysis

Consistent with the previous two questions, we follow the same correlation analysis for filtering and organizing the factors and obtain the matrix of correlation coefficients as follows.

Figure 17: The Heatmap of Factors Affecting Pet Food Industry



As can be seen from the above figure, the correlation between the factors and the number of cats is strong, with correlation between the factors and the number of of dogs is relatively weak. In conclution, the total number of pets, China market size and global market size have significant correlations on the total output value and total export value of pet food in China, while the household penetration rate has a relatively small impact on pet food, so we do not take this factor into account in the model. Therefore, we can summarize the better fit for the two models in the following Table 10.

Table 10: Affecting Factors

Factors affecting production	Factors affecting export
Per capita GDP The exchange rate of RMB against US dollar Total number of pets (in millions) China pet food market size (in 100 millions dollars) Global pet food market size (in 100 millions dollars)	Per capita GDP Proportion of pet food exports of all merchandise eports

5.3 Projected Results

5.3.1 Forecasting Pet Food Production

In this section, we mainly use a single Multiple Linear Regression Model. Construct a Multiple Linear Regression Model to predict the China pet food production value.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \tag{7}$$

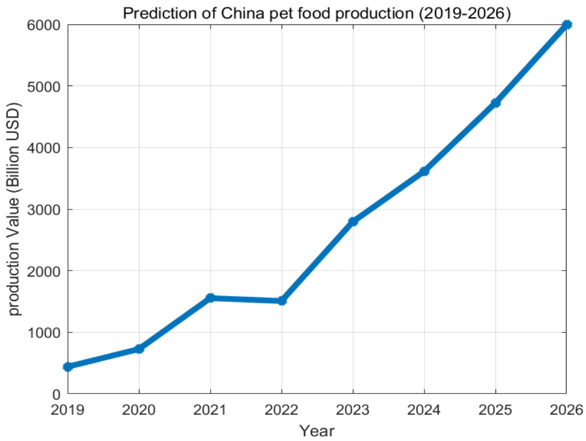
X_1, X_2, X_3, X_4, X_5 refer to the total number of pets, China pet food market size, global pet food market size, per capita GDP in China, the exchange rate of RMB against US dollar respectively, while y refers to the projected value of China's pet food production for the next three years(in USD).

The projected result is showed as follows:

Table 11: Projected Results

Year	2024	2025	2026
Pet food production (in USD)	3612.24	4722.82	5993.98

Figure 18: Prediction of China pet food production



As can be seen from the result, China pet food production will remain on an upward trend for the next three years, which indicated that China will reduce its dependence on imported pet food, revealing the vibrant pet food industry in China.

5.3.2 Forecasting Pet Food Export

In this section, we construct the a composite model of Support Vector Regression (SVR) [1] and Random Forest Regression [2] to make predictions, then determine the weights using the Particle Swarm Optimization algorithm to optimize the composite model, and finally apply the algorithm to make predictions of the total value of pet food exports over the next three years.

- Support Vector Regression

Support Vector Regression (SVR) is an extension of Support Vector Machines (SVMs) and is mainly used for regression analysis, i.e., predicting continuous numerical objectives.

$$f(X)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(X_i,X)+b \tag{8}$$

In this formula, X_i is the i-th sample in the training data, α_i,α_i^* are Lagrange multiplier, $K(X_i,X)$ is kernel function, b is bias entry respectively.

- Random Forest Regression

Random forest is an integrated learning algorithm, which can effectively reduce the risk of overfitting and ensure model stability and prediction accuracy by integrating multiple decision trees, using self-service sampling method (Bootstrap), randomly selecting a subset of features, and voting mechanism to make predictions.

$$\hat{y}=\frac{1}{T}\sum_{t=1}^{T}f_t(X) \tag{9}$$

In this formula, T is the number of decision trees in a random forest, $f_t(X)$ is the prediction of input feature X by the t-th tree, $\hat{y}$ is the projected value of pet food expenses.

Since we need to combine the two models into a optimized composite model, we apply the Particle Swarm Optimization algorithm to calculate the weights of each model. After the solving process, we obtain the following result.

Table 12: Result1

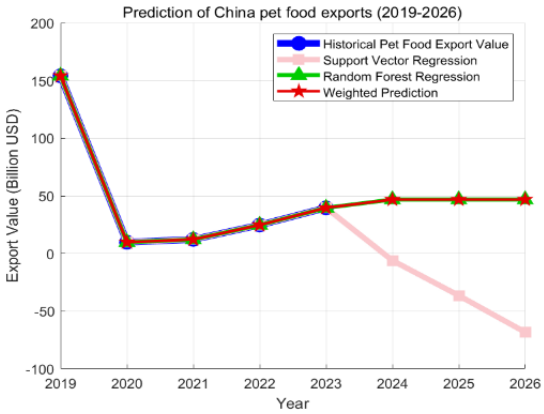
W1	W2
2.372476804339931E-06	0.999997627523196

In this case, W1 is the weight of the support vector regression, W2 is the weight of the random forest regression.

Table 13: Result2

Year	2024	2025	2026
Exports (in billion USD)	46.793474	46.793402	46.793327

Figure 19: Prediction of China pet food exports



From the table we can see, the projected values of exports for the next three years almost stay the same. However, we can still see a certain downward trend in the volume of exports. By solving the first question as well as the second, we can surmise the reason for this trend may be that the growth in domestic demand for pet food may have exceeded the growth in domestic production of pet food in certain extent.

6. Task 4: Sustainable Development Strategy

6.1 Correlation Analysis

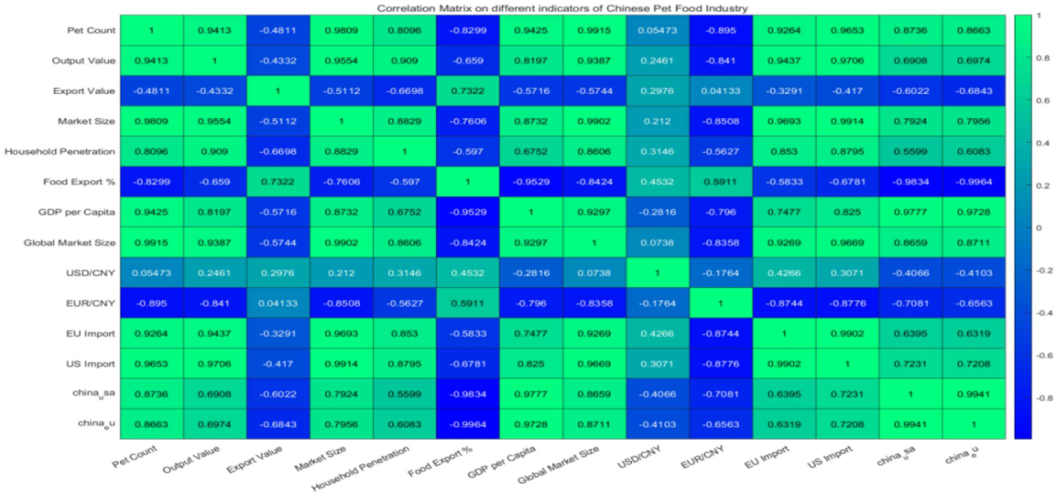
China's pet food industry will unavoidably be affected by new foreign economic policies (e.g. tariff policies) in European countries and the United States. In order to quantitatively analyze this impact, develop an appropriate mathematical model, taking into account the data given and collected, as well as the calculations in the above question. Based on the calculations, develop a feasible strategy for the sustainable development of China's pet food industry.

Table 14: Economic policies

Year	2019	2020	2021	2022	2023
U.S. MFN tax rate	0	0	0	0	0
U.S. imposes tariffs on China	0.25	0.25	0.25	0.25	0.25
EU MFN rate	0	0	0	0	0
EU raises tariffs on China	None	None	None	None	None
Quantitative restrictions on imports	None	None	None	None	None
FTA	None	None	None	None	None
Exchange rates(USD/CNY)	6.9	6.9	6.45	6.75	7.12
Exchange rates (EUR/CNY)	7.75	8.02	7.65	7.5	7.34
Total EU pet food imports (EUR billion)	20.5	21	22	24.4	27.2
Total U.S. pet food imports ($ billion)	15.3	16	17.5	19	21.3
Bilateral trade between China and Europe ($ billion)	5831	6495	8285.9	8473	7830
Bilateral trade between China and the United States ($ billion)	5413.8	5603.54	6735	6906	6486.86

First, we collect relevant economic policy data for quantitative analysis: correlation analysis. The results of the analysis are shown below:

Figure 20: Correlation Matrix on different indicators



6.2 Model Building

6.2.1 Support Vector Regression Model

Considering the correlation analysis of the above influencing factors, we use the Support Vector Regression model(SVR) to predict the total value of China's pet food exports in the future by predicting the proportion of future food exports, the exchange rate (USD/CNY), and we analyze and predict the exports to the United States as an example.

Figure 21: China pets exports values(2024-2026)

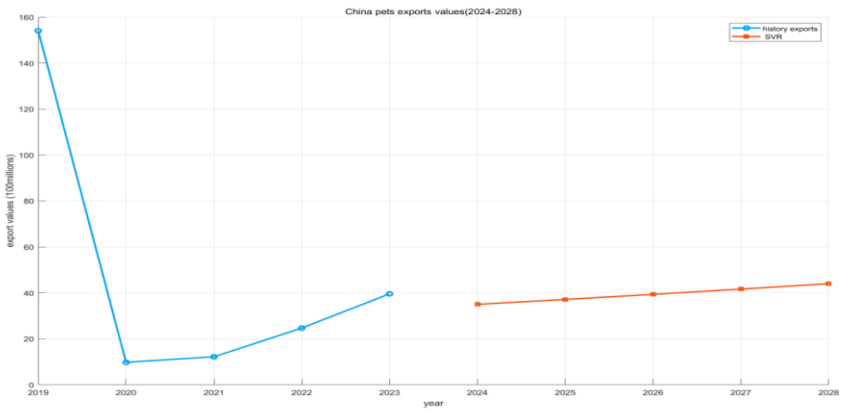


Table 15: Results (100 millions USD)

2024	2025	2026	2027	2028
35.0357	37.1812	39.39	41.6639	44.00

As is seen from above, the total value of China's pet food exports is expected to continue to grow in 2024-2026, likely due to increased demand for pet food in the U.S. market and improved price competitiveness as a result of changes in the exchange rate.

6.2.2 T-test

In order to quantify exactly in which years China's pet food industry was affected by what policies, we take 2020 as the node and use the data collected in the first three questions and in the appendix to conduct a T-test. T-test is generally used to compare whether there is a significant difference between the means of two independent samples. In this question, we use the T-test to analyze the performance of China's pet food industry under different policy contexts between 2019 and 2023, especially whether there is a significant difference in industry volatility before and after the policy change.

The underlying assumptions of the T-test are:

①Null hypothesis (H_0): The means of the two sets of data are equal, i.e. there is no significant difference in the performance of the industry before and after the policy change.

②Alternative hypothesis (H_1): The means of the two data sets are not equal, i.e., there is a significant difference in the performance of the industry before and after the policy change.

The statistic for the T-test is calculated as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^{\ 2}}{n_1} + \frac{s_2^{\ 2}}{n_2}}} \tag{10}$$

- $\bar{X}_1$ and $\bar{X}_2$ are the means of the two samples, respectively.
- $s_1^{\ 2}$ and $s_2^{\ 2}$ are the variances of the two sets of samples, respectively.
- n_1 and n_2 are the sample sizes of the two groups of samples, respectively.

If the calculation of the hypothesis test indicates that the p-value is less than the level of significance (usually 0.05) then the null hypothesis can be rejected and the means of the two groups of samples can be considered to be significantly different.

The results of the analysis are shown below:

Table 16: Around 2020

	F	Significance	t	Degrees of Freedom	Sig. (two-tailed)
Assuming equal variance	1.094	0.355	-0.556	4	0.608
Not assuming equal variance			-0.676	3.501	0.541

Not assuming equal variance, sig.(two-tailed)>0.05, the difference between the two groups is not significant.

Table 17: Around 2021

	F	Significance	t	Degrees of Freedom	Sig.(two-tailed)
Assuming equal variance	0.861	0.406	-0.639	4	0.558
Not assuming equal variance			-0.764	3.369	0.495

Not assuming equal variance, sig.(two-tailed)<0.05, the difference between two groups is significant.

In summary, there is a significant difference in China's pet food export volume around 2021-2022. For the United States, although the early tariff increases have a small direct impact on pet food, the subsequent export controls on high-tech areas and the complexity of the overall trade environment have indirectly increased the uncertainty of China's pet food exports. This uncertainty may lead exporters to adjust their export volumes in the face of higher risks and costs.

6.3 Practical Strategies

First, based on the above analysis, it can be seen that the overall development trend of China's pet industry continues to grow, and as consumers' demand for pet health and nutrition improves, the market demand gradually transforms to high-end pet food. We predict that the demand for pet food in China will continue to grow in the next three years. Therefore, China's pet food industry should strengthen the research and development and production of high-end products, especially in natural and organic food and special functional food, which have great market potential and can effectively meet the escalating consumer demand.

Secondly, after analyzing the development of the global pet industry, especially the European and American markets, it can be found that the European and American pet markets are highly mature and continue to expand, especially in the field of pet food, where demand remains strong. According to the forecast data for the next three years, the global demand for pet food will continue to grow especially in the field of high-quality, customized and specific nutritional needs, which opens up a broader international market for Chinese pet food enterprises. Therefore, Chinese companies should actively promote the internationalization strategy of their products and expand overseas markets, especially those with higher demand, such as Europe and the United States. In this process, it is necessary to focus on brand building and market positioning, and strive to establish brand influence through innovation, quality, environmental protection and other differentiation advantages.

7. Model Validation and Evaluation

7.1 Error Analysis

We utilize two evaluation metrics to comprehensively assess and compare the predictive performance of the model. They are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error(RMSE).

- Mean Absolute Percentage Error (MAPE)

MAPE calculates the mean percentage of absolute error between predicted and actual values. It reflects the degree of deviation of the predicted value relative to the actual value and is a dimensionless quantity that facilitates comparisons between different data sets.

$$MAPE = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{11}$$

y_i is the real value, $\hat{y}_i$ is the forecast value, n is number of data points.

- Root Mean Square Error (RMSE).

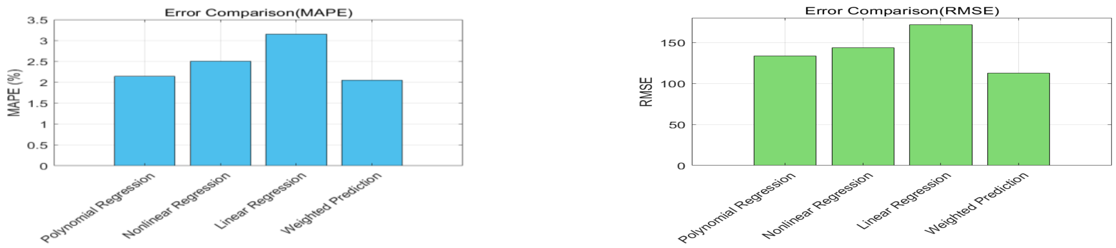
RMSE calculates the square root of the mean of the squares of the differences between the predicted and actual values. It reflects the degree of dispersion of the prediction error and is a quantitative quantity with the same units as the data.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y}_i)^2} \tag{12}$$

y_i is the real value, $\hat{y}_i$ is the forecast value, n is number of data points.

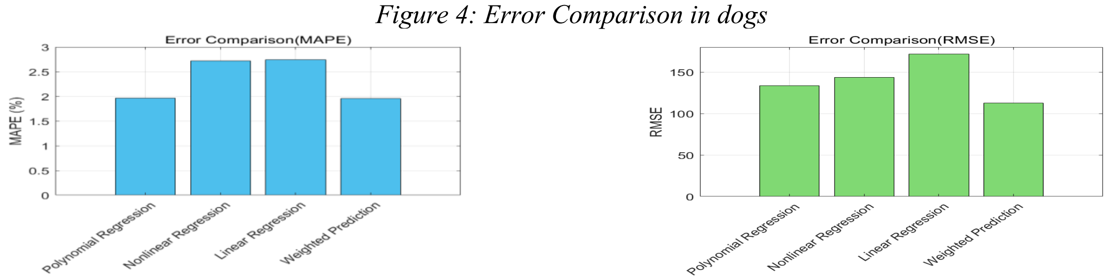
➢ Comparison of errors in cats

Figure 3: Error Comparison in cats



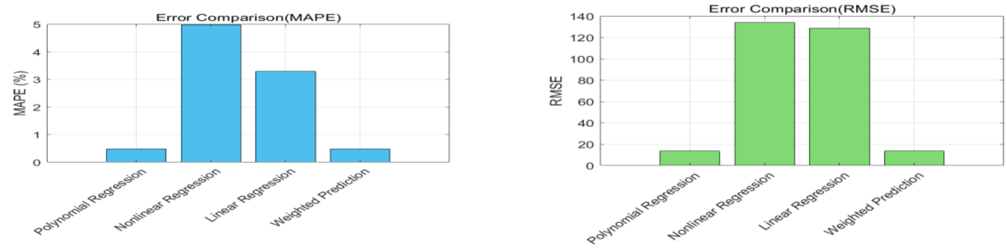
➢ Comparison of errors in dogs

Figure 4: Error Comparison in dogs



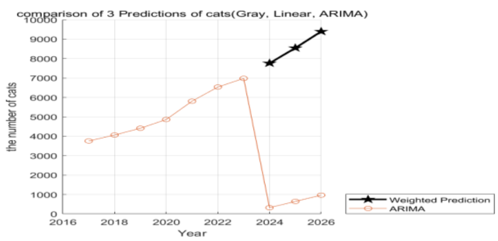
➢ Pet Related Business Market Size Forecast

Figure 24: Error Comparison in Pet Related Bussiness Market Size Model Evaluation

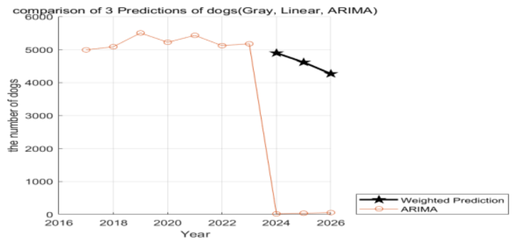


We compare the ARIMA model with the Weighted Prediction Model constructed above.

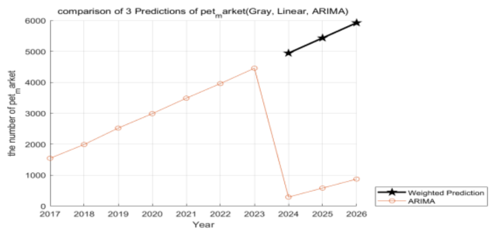
Figure 25: Comprison of 3 Predictions



(a) cats



(b) dogs



(c) Pet-related Business Market Size

8. Advantages and Disadvantages Analysis

8.1 Strengths

(1) We combine Linear Regression, Nonlinear Regression, and Polynomial Regression Models to enhance the degree of model fit and the predictive accuracy and stability of the models.

(2) We compare the ARIMA model with the Weighted Prediction Model we constructed and conclude that the model we constructed predicts better.

(3) We use Swarm Particle Optimization Algorithm to determine the different weights of several conventional models in the comnition, so that our self-developed model model is close to optimal solution.

8.2 Weaknesses

(1) It’s impossible to take all factors into account in the model, resulting in inevitable errors in our predictions.

(2) The collected sample size of data is limited , can be expanded further to obtain more accurate prediction.

9. Conclusion

This study develops a multi-model analytical framework to forecast China’s pet industry and quantitatively assess the impact of foreign economic policies on its pet food exports. The main findings are as follows. By

2026, China's pet cat and dog populations are projected to reach 93.95 million and 42.66 million, respectively. China's pet food production and export values are expected to reach 5,993.98 and 46.79 (100 million USD) by 2026. Under foreign tariff policy shifts, exports are predicted to be 44 (100 million USD) by 2028, and a significant difference in export values is observed around 2021. These results highlight the strong growth potential of China's pet industry and its vulnerability to external policy changes.

The predictions rely on simplified assumptions such as fixed GDP growth rate and exchange rate trends. The data span is limited to 2019–2023, and some potential disruptive factors including disease outbreaks and sudden regulatory changes are not incorporated. Future research should extend the time horizon, include scenario-based uncertainty analysis, and cover other pet-related sectors such as pet medical care and supplies. For sustainable development, we recommend diversifying export markets, strengthening domestic brand competitiveness, and building supply chain resilience to mitigate policy-driven risks.

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Conflicts of Interest

The authors declare no conflict of interest.

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