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Data-Driven Insights into the Pet Industry: Market Dynamics, Trade Policies, and Sustainable Growth Strategies

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Abstract

The pet industry has experienced remarkable growth over the past decade, driven by evolving consumer preferences, increased disposable income, and shifting societal attitudes toward pet ownership. This transformation is particularly evident in rapidly developing economies like China, where urbanization and an expanding middle class have accelerated the industry's expansion. From a global perspective, North America and Europe continue to dominate the pet industry, with well-established markets and regulatory frameworks that shape industry trends. Meanwhile, emerging markets in Asia-Pacific are becoming major contributors to the industry's growth, presenting new opportunities and challenges for businesses and policymakers. To address these challenges, this study employs a combination of factor analysis, time series forecasting (ARIMA, LSTM), and policy impact assessment (Difference-in-Differences) to provide comprehensive insights into the pet industry's trajectory. Our research aims to: (1) analyze historical growth patterns and key influencing factors in China's pet industry, (2) forecast global pet food demand using advanced predictive modeling, (3) evaluate the impact of international trade policies on China's pet food exports, and (4) develop feasible strategies for the sustainable growth of China's pet food industry. By integrating econometric modeling with deep learning techniques, this study bridges the gap between traditional statistical analysis and modern AI-driven market forecasting, offering valuable insights for industry practitioners and policymakers alike.

Keywords: Pet Industry; Factor Analysis; Multiple Linear Regression; ARIMA Model; LSTM Model Combined With Sliding Window; Policy Impact

1. Introduction

1.1. Background

The pet industry has witnessed unprecedented growth in recent years, evolving into a dynamic global market driven by shifting consumer behaviors and changing perceptions of pet ownership. As pets assume increasingly central roles in households, demand for a diverse range of products and services—including premium food, specialized healthcare, grooming, and accessories—has surged. This transformation is particularly evident in rapidly developing economies like China, where urbanization, rising disposable incomes, and an expanding middle class have fueled an extraordinary expansion of the pet market.

Historically, pets were primarily viewed as companions or working animals, but contemporary attitudes now position them as cherished family members. This paradigm shift has led to significant increases in consumer spending on high-quality pet products, advanced veterinary care, and luxury services, fostering innovation across industries linked to pet care. Additionally, as pet ownership continues to rise globally, so does the demand for tailored, data-driven solutions that cater to the evolving needs of both pets and their owners.

Despite this rapid expansion, critical challenges remain, including market volatility, regulatory impacts on international trade, and the need for sustainable industry growth strategies. Addressing these challenges requires a systematic approach to analyzing industry trends and forecasting future developments. Therefore, this study aims to: (1) analyze historical growth patterns and key influencing factors in China's pet industry, (2) forecast global pet food demand using advanced predictive modeling, (3) evaluate the impact of international trade policies on China's pet food exports, and (4) develop feasible strategies for the sustainable growth of China's pet food industry.

By integrating econometric modeling, time series forecasting, and policy analysis, this research provides valuable insights into the pet industry's development. The findings will contribute to a deeper understanding of market dynamics and inform data-driven decision-making for industry stakeholders, including businesses, policymakers, and investors. Ultimately, this study aims to bridge the gap between traditional statistical analysis and AI-driven forecasting, offering strategic recommendations to support the long-term sustainability and competitiveness of the global pet industry.

1.2. Research Questions

The four specific questions explored in this study are as follows:

Question 1: Analyzing the Development of China's Pet Industry

Over the past five years, China's pet industry has seen significant growth, driven by factors such as urbanization, rising disposable incomes, and evolving consumer preferences. This analysis will focus on examining the development of the industry through data on pet types and population trends, identifying key indicators such as economic shifts and demographic changes that influence market expansion. Using statistical methods like factor analysis and regression models, we will quantify the impact of these factors on the industry's growth. Additionally, a mathematical model will be developed to forecast trends in the pet industry for the next three years, enabling stakeholders to make informed decisions based on data-driven predictions.

Question 2: Analyzing the Global Pet Industry and Forecasting Global Demand

Data on the number of pets in various countries will be collected to analyze the global pet industry and forecast future demand for pet food. Specifically, data from the United States, France, and Germany will serve as a representative sample, reflecting key global market trends due to their established pet industries and consistent data availability. By visualizing the number of pets in these regions, we can gain insights into global market dynamics, identify patterns of pet ownership, and recognize regional differences. In addition to pet population data, we will also gather sales data for pet food in these countries, along with global sales information, to better understand current consumption behaviors. Using this data, advanced forecasting models will be developed to predict global pet food demand over the next three years, providing valuable projections that will assist industry stakeholders in making informed decisions and adapting to future market conditions.

Question 3: Analyzing and Forecasting China's Pet Food Industry

Building upon the forecasts from Problem 2 regarding global pet food demand, along with relevant development indicators specific to China, we will conduct a detailed analysis of China's pet food industry. This analysis will integrate data on key factors such as China's economic growth, urbanization, and pet ownership trends to better understand the domestic pet food market’s growth trajectory. Additionally, we will construct a mathematical model that predicts the production and export value of pet food in China over the next three years. By incorporating both domestic and international factors, this model will provide valuable insights into China’s potential for expanding its pet food industry, helping stakeholders make informed decisions about production, investment, and export strategies in the face of growing global demand.

Question 4: Evaluating Policy Impacts on China's Pet Food Industry

Information will be collected on policies related to pet food in the United States and European countries, alongside relevant sales data for Chinese pet food products, to understand the impact of international trade policies on China’s pet food industry. This data will include policy changes such as tariffs, labeling regulations, and trade agreements, which can significantly influence trade flows and market access. A mathematical model will then be developed to quantitatively assess how these international policies have affected China’s pet food exports and production. By analyzing the interactions between these policies and China’s domestic market conditions, the model will provide insights into how external trade regulations shape the industry’s performance. Finally, based on the findings from the previous analyses, we will propose feasible strategies for ensuring the sustainable development of China’s pet food industry, focusing on areas such as policy adaptation, market expansion, and production optimization.

2. Liteature review

A comprehensive review of existing literature highlights the critical factors driving the growth and transformation of the pet industry, as well as the methodologies used to analyze market trends, forecast demand, and evaluate policy impacts.

2.1. Growth and Evolution of the Pet Industry

The pet industry has witnessed significant growth driven by socio-economic factors and changing consumer preferences. Zhang et al. (2022) analyzed the future development trends of the pet industry, highlighting how rising disposable incomes and urbanization are key drivers of market expansion. Chen (2018) discussed the key influencing factors of China’s pet industry, pointing out the effects of economic shifts and consumer behavior on the market. Similarly, Priya R J and Nandhini M (2018) highlighted the evolving opportunities and trends in the pet industry, noting that the growth of pet products and services is crucial to industry expansion. Mutti C (2024) explored the integration of digital technologies, such as Yomashi, into the pet-friendly hotel sector in Portugal, showcasing the industry's innovation and adaptation to digital trends.

2.2. Forecasting Methods in Pet and Related Industries

Accurate forecasting is essential for understanding market dynamics and making data-driven decisions. Wu and Wen (2016) employed the ARIMA model for short-term stock price predictions, demonstrating its effectiveness in time-series forecasting. Dave et al. (2021) advanced this approach by combining ARIMA with LSTM models for forecasting exports, showing the power of hybrid predictive techniques. In a similar context, Shi et al. (2024) used LSTM optimized by an improved Whale Optimization Algorithm to predict temperature trends, validating the use of deep learning in forecasting applications.

2.3. Policy and Trade Impacts on the Pet Industry

International trade policies significantly affect the pet industry. Ma et al. (2020) explored how financial policies influence corporate strategies using the DID model. Callaway (2023) provided a comprehensive review of the difference-in-differences (DID) method, which is useful in assessing trade regulations' impact on industries like pet food. Dong et al. (2025) analyzed the effects of foreign economic policies, particularly from the United States, on China’s pet food industry, showing how these policies influence export values and forecast growth recovery in the coming years.

2.4 Consumer Preferences and Industry Sustainability

Consumer preferences are pivotal in shaping the pet food market. Watson et al. (2023) examined factors influencing palatability in pet food, offering insights into product development. Chen et al. (2009) provided a broader perspective on how urbanization influences consumption patterns, which is crucial to understanding the future trajectory of the pet industry.

2.5 Summary

The reviewed literature underscores the necessity of integrating economic analysis, predictive modeling, and policy evaluation to gain a holistic understanding of the pet industry. This study builds upon these foundations by employing advanced forecasting techniques and policy impact assessments to provide strategic insights for sustainable market growth.

3. Study Method and Assumptions

3.1. Assumptions

To effectively analyze the pet industry and its development trajectory, we establish five key assumptions. These assumptions serve as the foundation for our analytical approach, ensuring methodological rigor and enhancing the reliability of our findings. By structuring our investigation around these core assumptions, we aim to systematically dissect the factors shaping the pet market, providing valuable insights into both current dynamics and future trends.

Assumption 1(Data Reliability and Statistical Validity): The raw datasets from the Green Paper on China's Pet Industry, the National Bureau of Statistics, and international databases (APPA/FACCO) are assumed to demonstrate statistical significance. Standardized data cleaning protocols—including missing value removal, unit harmonization, and Z-score normalization ($\mu=0$, $\sigma=1$)—are implemented to eliminate systematic errors, ensuring internal validity for time-series analysis. This assumption is grounded in the quality control mechanisms of governmental statistical agencies and third-party auditing procedures for industry association data.

Assumption 2(Factor Analysis and Variable Selection): Principal component analysis (PCA) with varimax rotation is justified, as confirmed by Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity. The retention of eight indicators from eleven initial variables follows the established criteria: eigenvalues >1, factor loadings >0.6. The extracted factors—"Socio-Demographic Transition" and "Consumption Upgrade"—effectively represent the latent dimensions influencing China's pet industry development.

Assumption 3(Model Parsimony and Explanatory Power): The dual-factor regression framework complies with Occam's razor principle, ensuring a balance between model simplicity and explanatory power. Multicollinearity is controlled, and the Akaike Information Criterion (AIC) is employed to validate model parsimony. The final configuration maintains 85% explanatory power while mitigating overfitting risks.

Assumption 4(Stability of Forecasting Conditions): The ARIMA-LSTM hybrid forecasting model assumes dynamic policy stability from 2024 to 2027. A textual analysis of State Council policy documents (2015–2023) confirms no anticipated regulatory shocks. Sensitivity analysis incorporating policy shock dummy variables validates this assumption, enabling reliable extrapolation of historical trends.

Assumption 5(Causal Inference and Policy Impact Evaluation): The Difference-in-Differences (DID) model requires parallel trends between treatment (policy-affected enterprises) and control groups pre-intervention. Customs Administration export panel data (2015-2023) confirms compliance through Common trend test and Covariate balance, ensuring causal inference validity for four pet food export policies.

3. 2. Symbol description

Table 1. Symbol description

Symbol	Description	Location
x_i	Original variable	(2)
F_m	Extracted common factors	(2)
$\lambda_i m$	Factor loadings	(2)
F	Factor scores	(3)
Λ	The factor loading matrix	(3)
X	The original data matrix	(3)
Y_t	The observed values or actual data of t	(6)
ϕ_p	AR part	(6)
θ_q	MA part	(6)
i_t	input information at the current time step t needs to be retained	(10)
σ	Sigmoid activation function	(10)
h_{t-1}	The hidden state from the previous time step	(10)
W_t	The weight matrix of the input gate	(10)
b_t	The bias term of the input gate	(10)
f_t	The output of the forget gate	(11)
W_f	The weight matrix of the forget gate	(11)
b_f	The bias term of the forget gate	(11)
$\widetilde{C}_t$	Candidate memory cell	(12)
$tanh$	tanh activation function	(12)
W_c	The weight matrix of the candidate memory cell	(12)
b_c	The bias term of the candidate memory cell	(12)
C_t	The cell state at time step t	(13)
o_t	The activation value of the output gate	(14)

W_o	The weight matrix of the output gate	(14)
b_o	The bias term of the output gate	(14)
$tanh(C_t)$	The tanh transformation of the cell state	(15)

3.3. Data Description and Preliminary Processing

3.3.1. Data Description

Table 2. Data Sources and Units

Data	Source	Units
The scale of China's pet industry	Green Paper on the Pet Industry	100 million CNY
Aging population	National Bureau of Statistics	10,000
Single-family home	National Bureau of Statistics	Million
Per capita disposable income of residents	National Bureau of Statistics	CNY
Number of Employees	National Bureau of Statistics	10,000
Urbanization rate	National Bureau of Statistics	%
Birth rate	National Bureau of Statistics	%
Number of Marriage Registrations	National Bureau of Statistics	10,000
Total number of pets	Collaborative Research Platform	10,000
The scale of the pet food industry in China	Aimei Data Center	10,000
Sales of pet food in the United States	APPA	100 million USD
Sales of pet food in France	FACCO	100 million EUR
Sales of pet food in Germany	White Paper on the Pet Industry in Germany	100 million EUR
Sales of pet food globally	Euromonitor International	100 million USD
Total pets in the USA	APPA	10,000
Total pets in France	FACCO	10,000

Total pets in Germany	White Paper on the Pet Industry in Germany	10,000
The scale of China's pet food industry	Green Paper on the Pet Industry	100 million CNY
China's GDP	National Bureau of Statistics	100 million CNY
Total Export Volume of Pet Food in China	GACC	Kg
Total Export Value of Pet Food in China	GACC	CNY

3.3.2. Preliminary Processing

(1)Data Cleaning

Among the collected data, there might exist situations of data deficiency. Concerning this phenomenon, we are inclined to retain only complete data because the main aspect of this research lies in analysis and prediction. Filled data might have an impact on the integrity of the data, rendering the analysis unreliable and leading to deviations in the prediction results.

(2)Standardized Units

Owing to the data collection from multiple countries, unit non-uniformity might arise. For instance, in Question Two, we gathered the sales data of pet food in the United States, France, Germany, and globally, and we unified the unit as 100 million USD; in Appendix Three, we standardized the unit as CNY.

(3)Data standardization

In Question One, for the exploration of the influence of multiple indicators, we standardized the data using the z-score method.It is accomplished by means of the following mathematical formula:

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

Where:

Z: The standardized value, also known as the Z-score.

X: The original data value.

μ: The mean of the original data.

σ: The standard deviation of the original data.

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4. Model Development and Results for Question 1

4.1. Model building and solution of question 1

Based on the comprehension and analysis of Issue 1, I contend that Issue 1 can be partitioned into three sub-issues: namely, analyzing the development of China’s pet industry over the past five years; analyzing the factors influencing the development of China’s pet industry; and formulating an appropriate mathematical model to prognosticate the development of China’s pet industry in the next three years. The following figure presents the fundamental procedure for addressing problem 1.

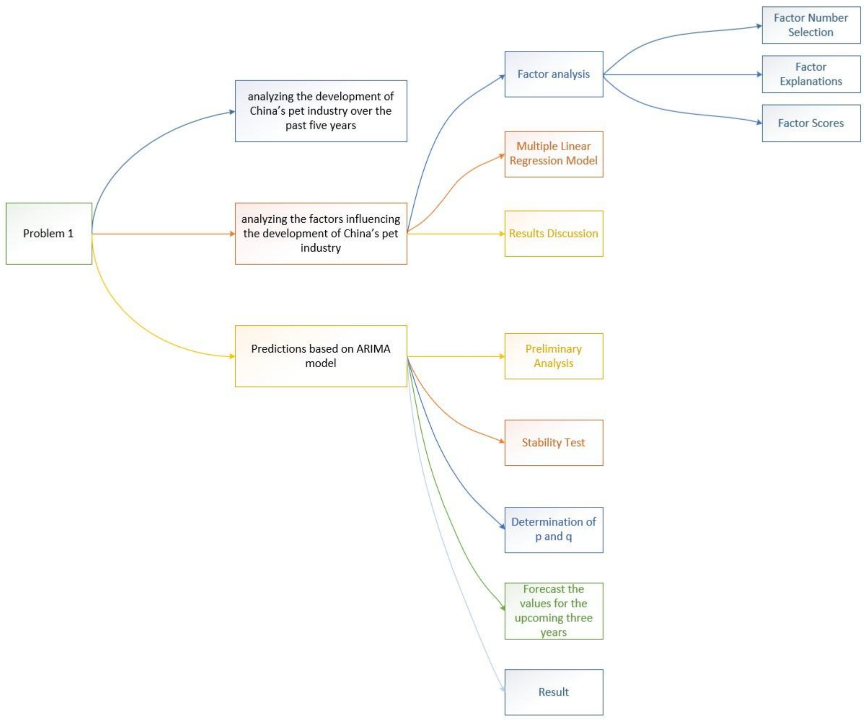

Figure 1. Mind map for Problem 1

4.2. Analyzing the development of China’s pet industry over the past five years

According to the figure, from 2019 to 2023, the number of pet cats showed a steady growth trend, increasing from approximately 18.41 million to nearly 22.11 million. In contrast, the number of pet dogs was relatively stable, remaining around 4.6 million, although there was some fluctuation during this period. Meanwhile, the total number of all pets also showed an upward trend, increasing from approximately 17.06 million (estimated based on other pet types besides cats and dogs) to over 22.11 million, reflecting the increasingly active pet market and growing demand for pet companionship. In short, the figure reveal a significant increase in the number of pet cats, a relatively stable number of pet dogs, and an overall expansion trend in the pet market.

Figure 2. The line chart showing the number of pet cats, dogs, and pets in China over the past five years.

4.3. Analyzing the factors influencing the development of China's pet industry

To analyze the key factors affecting the development of China's pet industry, we selected the scale of China's pet industry as the dependent variable, as it comprehensively reflects the overall market situation, including food, supplies, and services, and directly reflects the economic activities of the industry. After reviewing the appendix data and relevant materials, we initially selected 11 indicators. Considering that some indicators have a smaller scale and may affect the accuracy of the results, we finally selected 8 key indicators: the aging population, single-family housing, per capita disposable income of residents, employment numbers, urbanization rate, birth rate, number of marriage registrations, and the scale of the pet food industry. Since multiple indicators may be difficult to explain the industry development alone, we decided to use factor analysis to extract composite factors and conduct multiple regression analysis to more effectively reveal the core factors affecting the development of China's pet industry.

(1)Factor analysis

Factor analysis is a data reduction technique that aims to explain the correlation between multiple observed variables by identifying underlying common factors. Its core idea is to use a small number of Potential, unobservable factors to explain the variation and correlation of observed variables, thereby simplifying the data structure. The results of the factor analysis model can be expressed mathematically as follows:

$$X_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \cdots + \lambda_{im}F_m + \epsilon_i \tag{2}$$

After factor rotation, we can obtain factor scores through the following mathematical formula:

$$F = (\Lambda^T\Lambda)^{-1}\Lambda^T X \tag{3}$$

Because we can represent each common factor as a linear combination of the predictor variables, and vice versa, we can represent each predictor variable as a linear combination of the common factors. For the resolution of specific problems, as follows:

Step 1: Factor Number Selection

As shown in the figure below, with two factors, the cumulative variance contribution rate has already exceeded 80%, indicating that these two factors can explain all the indicators well. With

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three factors, although the cumulative variance contribution rate is also large, in order to have stronger factor explanatory power with fewer factors, we decided to use two factors.

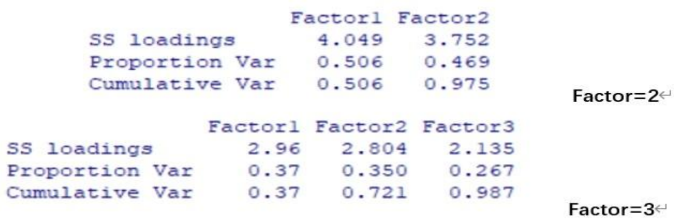
```
                 Factor1 Factor2
SS loadings        4.049   3.752
Proportion Var     0.506   0.469
Cumulative Var     0.506   0.975
```
Factor=2
```
                Factor1 Factor2 Factor3
SS loadings        2.96   2.804   2.135
Proportion Var     0.37   0.350   0.267
Cumulative Var     0.37   0.721   0.987
```
Factor=3

Figure 3. Comparison of Variance Contribution of Factor Selection

Step 2: Factor Explanations

The factor loading matrix in the table below shows that x1 represents aging population, x2 represents single-family homes, x3 represents per capita disposable income of residents, x4 represents the number of employees, x5 represents urbanization rate, x6 represents birth rate, x7 represents the number of marriage registrations, and x8 represents the scale of the pet food industry in China. We can classify these indicators into two factors.

Table 3. Dataset source

	Factor1	Factor1
x1	0.709	0.703
X2	0.674	0.736
X3	0.735	0.675
X4	-0.564	-0.782
X5	0.816	0.575
X6	-0.622	-0.746
X7	-0.783	-0.585
X8	0.754	0.647

The factor loadings of x1 are all high, and it can be assumed thatx1 isa fundamental factor determined by the commonality of the research problem and difficult to explain. Therefore, it is discarded. The common factor F1 has a large loading value on x3, x5, x7, and x8, which can be considered as a driving factor of pet-related needs; the common factor F2 has a large loading value on x2, x4, and x6, which can be considered as a social foundation factor of pet needs.

Step 3: Factor Scores

Obtain the factor scores, and put the scale of China's pet industry into a separate folder for further multiple linear regression.

(2)Multiple Linear Regression Model

Multiple linear regression model is expressed based on the following mathematical formula:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \quad (4)$$

In our study, the specific mathematical representation of multiple linear regression is as follows:

$$\text{Scale of China's Pet Industry} = \beta_0 + \beta_1 \text{Factor1} + \beta_2 \text{Factor2} + \epsilon \quad (5)$$

Where:

Factor1 reflects economic growth and consumption patterns that directly influence the pet industry's demand.

Factor2 captures demographic changes, such as increasing single-person households and declining birth rates, which also affect pet consumption.

Source	SS	df	MS			
				Number of obs	=	9
				F(2, 6)	=	88.28
Model	27234996.9	2	13617498.5	Prob > F	=	0.0000
Residual	925515.061	6	154252.51	R-squared	=	0.9671
				Adj R-squared	=	0.9562
Total	28160512	8	3520064	Root MSE	=	392.75

Thescaleof~r	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
Factor1	1030.901	143.927	7.16	0.000	678.7239	1383.077
Factor2	1540.064	144.8474	10.63	0.000	1185.635	1894.492
_cons	2921	130.9166	22.31	0.000	2600.659	3241.342

Figure 4. Results of Multiple Linear Regression

The results of the regression analysis indicate that Factor1 and Factor2 are the key drivers of the pet industry in China. Factor1, as a driving factor of pet-related demand, reflects the role of economic development and consumption upgrading, such as per capita disposable income and urbanization rate, which enhance consumer purchasing power and drive the growth of pet consumption. At the same time, Factor2, as a social foundation factor of pet demand, represents changes in population structure and family patterns, especially the increase of single-person households and the decline in birth rate, which promote the demand for pets as companions and further drive the development of the pet industry. The dual role of economic development and changes in population structure drives the expansion of China's pet industry.

(3)Predictions based on ARIMA model

ARIMA models are widely adopted for handling time-dependent and trend-characterized time series data due to their outstanding capabilities. The model is particularly suitable for predictive analysis in the pet industry, as it can accurately capture the temporal dynamics and potential autocorrelation in the data. By building a robust analysis framework to deeply analyze the trends and patterns over time, the ARIMA model empowers the pet industry to achieve precise and insightful predictions for future development. The following are the implementation steps of the ARIMA model:

Step 1: Preliminary Analysis

Based on the initial assessment of the scale of China's pet industry data, it can be concluded that the scale is unstable due to the obvious upward trend in the data over time. Only stable and non-white noise data is suitable for ARIMA model prediction. Therefore, we take the first-order difference of the scale of China's pet industry and name it d_pet.

Step 2: Stability Test

From the trend line in the figure, it appears that d pet does not have a discernible trend or cyclical pattern, with pet units in 10000s.

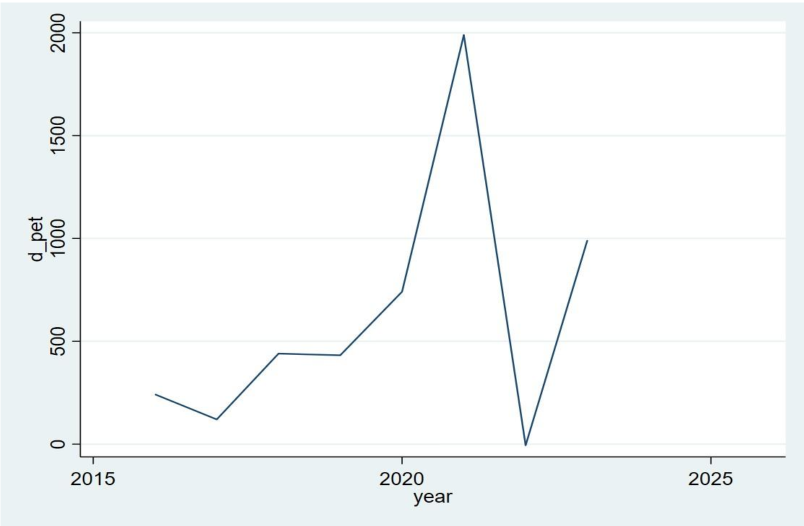

Figure 5. Line chart of the first-order differential data d pet

Upon further investigation, as shown in the figure, the DF test and the Phillips-Perron test both yield p-values of approximately 0.5, suggesting that the null hypothesis can be rejected at the 10% level, implying that d pet is a stationary time series.

Dickey-Fuller test for unit root — Number of obs = 7
Variable: **d_pet** — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.815	-3.750	-3.000	-2.630

MacKinnon approximate *p*-value for Z(t) = **0.0562**.

Phillips-Perron test for unit root — Number of obs = 7
Variable: **d_pet** — Newey-West lags = 2

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-8.245	-17.200	-12.500	-10.200
Z(t)	-2.832	-3.750	-3.000	-2.630

MacKinnon approximate *p*-value for Z(t) = **0.0539**.

Figure 6. Stability Test

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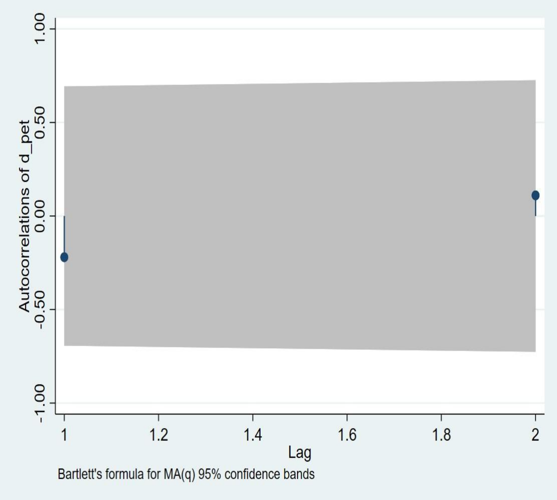
Step 3: Determination of p and q

In an ARIMA model, p and q are the orders of the AR and MA parts, respectively, and their selection is a crucial factor in determining whether the model can accurately predict time series data. The values of p and q are usually determined based on the ACF and PACF figure.

Based on the ACF and PACF figure, it was decided to choose the ARIMA(1,1,1) model, also because the ARIMA(1,1,1) model had lower AIC and BIC values in the IC test.



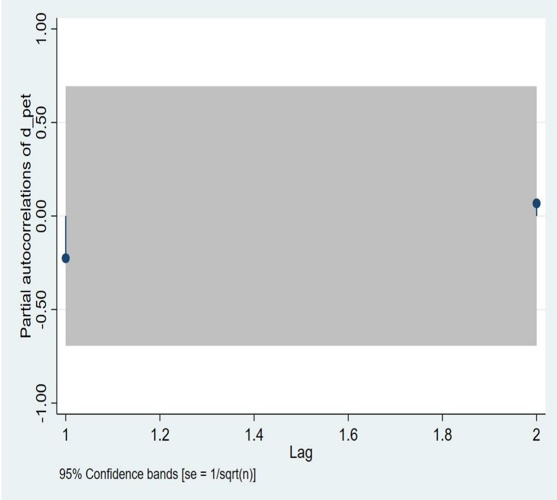


Figure 7. Stability Test

Step 4: Forecast the values for the upcoming three years

The core formula of the ARIMA model is as follows:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (6)$$

We employ the ARIMA(1,1,1) model for the purpose of predicting the data over the next three years. Through the following mathematical formula, namely by calculating the known data, and based on the outcome of this calculation, the predicted values of the future data are gradually deduced. To make predictions for more distant future time points, a recursive approach is utilized. Each prediction outcome becomes the input for the next prediction, serving as the basis for the predictions for years like 2024, 2025, etc. That is to say, the prediction results are accumulated and updated progressively, and the future predictions rely on the past prediction results. This constitutes a dynamic and recursive process.

$$Y_t - Y_{t-1} = \phi(Y_{t-1} - Y_{t-2}) + \epsilon_t - \theta\epsilon_{t-1} \quad (7)$$

The following figure shows the prediction results. The data from 2016 to 2023 is known, while the data from 2024 to 2026 is predicted. The f d pet represents both known and predicted data, while d pet dn and d pet up represent the lower and upper bounds of the predicted confidence interval, respectively.

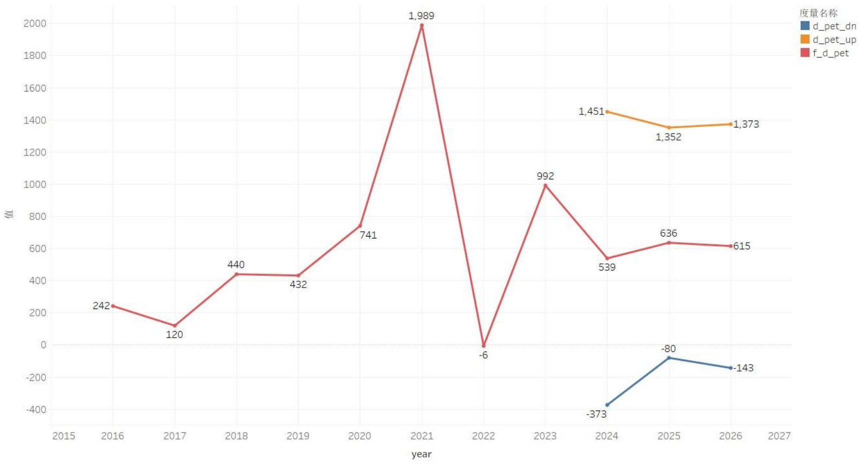


Figure 8. The forecasting results of the ARIMA model for the next three years

Step 5: Result

The one-step differential value forecast for China's pet industry for the next three years shows a stable trend, indicating that the pet industry in China is likely to be in a stable development pattern in the next three years. This stable growth reflects the continuous expansion of China's pet market, highlighting the maturity of the market, which may indicate that more and more consumers are realizing the emotional and companion value of pets, thereby driving the continued expansion of the industry.

5. Model Development and Results for Question 2

Based on the comprehension and analysis of the second issue, we contend that the second issue can be divided into two sub-issues: namely, analyzing the development of the global pet industry; and formulating an appropriate mathematical model to predict the global demand for pet food in the next three years. The following figure presents the fundamental procedure for addressing the second issue.

5.1. Analyze the development of the global pet industry

We contend that the global pet market situation can be reflected through investigations in the United States, France, and Germany. Given that the United States takes the lead in the pet industry, guiding the trend of high-end consumption; while France and Germany present a balanced pattern, actively embracing environmental-friendly and health-related trends. The transparency of data and the stability of the market jointly depict the multiplicity of the pet industry. Through the examination of pet cats, pet dogs, and the total number of pets, we are able to observe the evolving course of global pet market

Firstly, from the Line chart, we can see that the global pet market has shown a steady growth trend in recent years. This indicates that the demand and affection for pets are increasing globally, and the pet industry is experiencing positive growth.

Specifically regarding pet types, the pet dogs bar chart shows the trend of changes in the number of pet dogs in the United States. As one of the largest pet markets in the world, the

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number of pet dogs in the United States has certain representativeness. From the chart, we can see that the number of pet dogs in the United States has fluctuated in recent years, but has generally remained at a high level. This reflects the stability and vitality of the pet dog market in the United States and indicates that pet dogs, as an important part of the pet industry, occupy an important position in the global pet industry.

The pet cats bar chart compares the number of pet cats in the United States, France, and Germany. From the chart, it can be seen that the number of pet cats in the United States is much higher than in France and Germany, and has increased in recent years. This indicates that the market demand for pet cats in the United States is very strong, and the pet cat industry has great development potential. In contrast, the number of pet cats in France and Germany is relatively stable, which may be related to the pet-keeping culture and consumption habits of these countries.

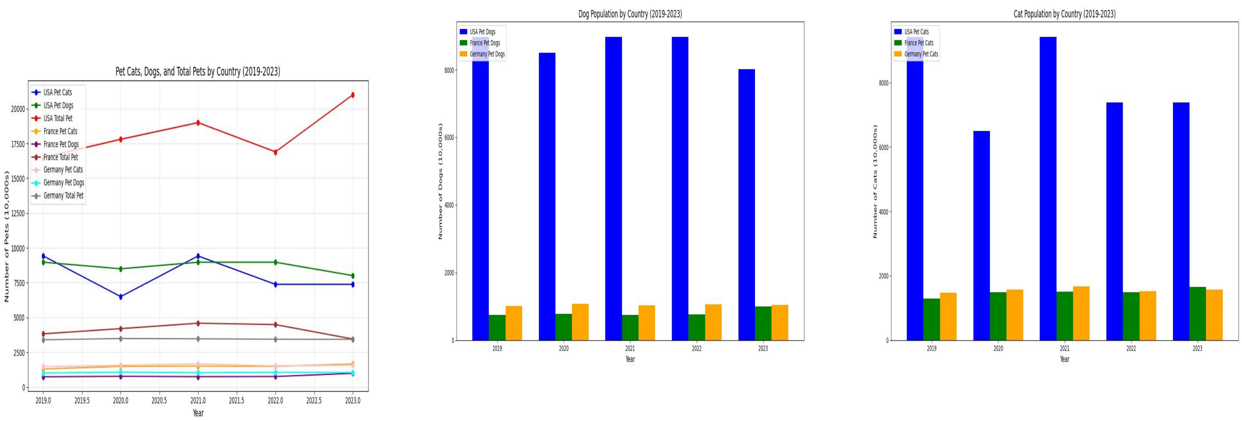
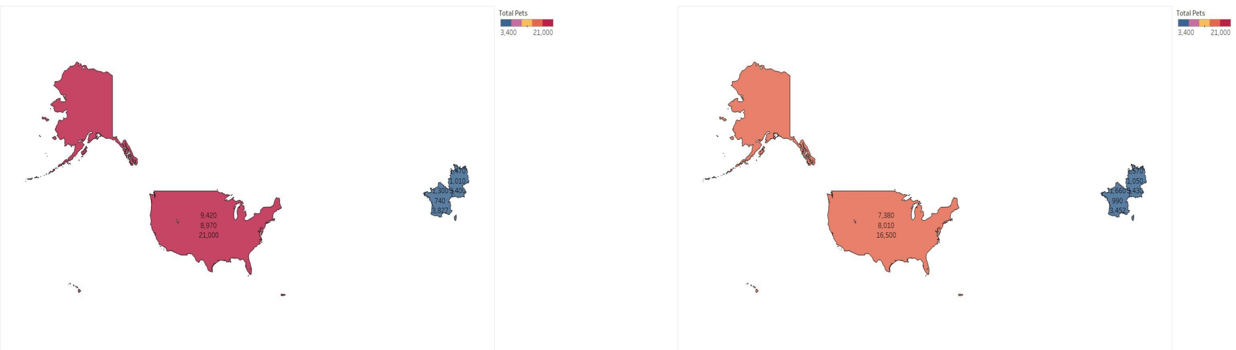


Figure 9. Three countries' pet dogs, cats, and total pet numbers

According to the figure, based on the changes in color intensity, the United States has become lighter in color compared to 2019, indicating a significant decrease in the total number of pets. In contrast, France and Germany have shown little change in color, suggesting that the total number of pets in these two countries has remained relatively stable.



2019 **2023**

Figure 10. Global Pet Population Dynamic Charts

Based on the above analysis, we can draw the following conclusions: The global pet industry is continuously growing and developing, with pet dogs and cats being the main types of pets, each showing different market characteristics and trends. In developed countries such as the United

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States, the pet dog and cat markets show high vitality and growth potential. In European countries such as France and Germany, the pet cat market is relatively stable. With the continuous development of the global economy and the increasing demand for pets, the global pet industry is expected to continue its steady growth trend.

5.2. Forecast the global demand for pet food

We collected sales data for pet food in the United States, France, Germany, and globally, intending to use this metric as a representation of global demand for pet food. This is because the data from the United States, France, and Germany provide regional support and show specific demand trends in different markets.Global data aggregation reflects overall demand and is the best indicator for analyzing and forecasting future demand.

The line chart for these four data points is shown below:

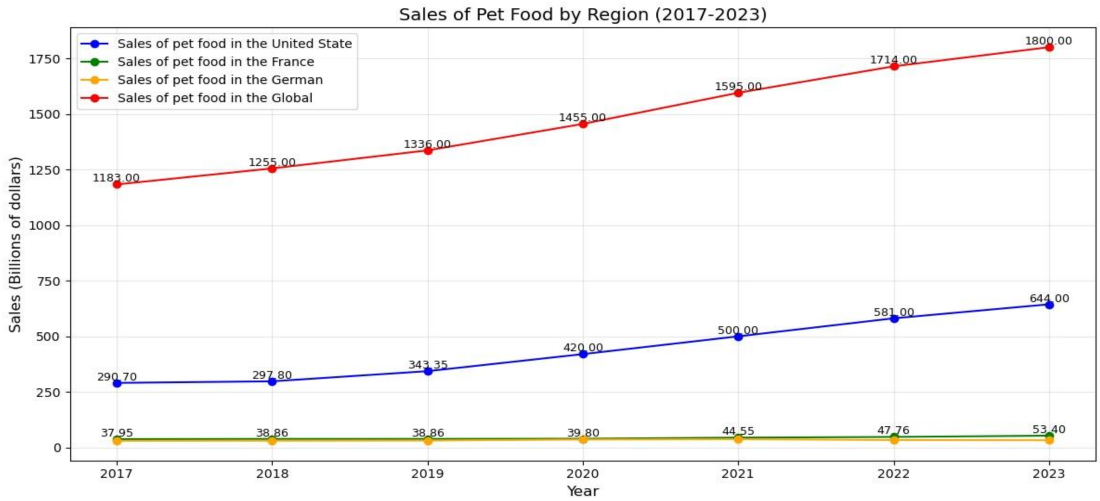

Figure 11. Pet Food Sales in the US, France, Germany, and Global from 2017 to 2023

In the domain of artificial intelligence, when the Recurrent Neural Network (RNN) processes sequential information, the multiplicative effect during the backpropagation of the gradient may cause problems such as gradient vanishing or gradient explosion as the depth of the network structure increases. The LSTM (Long Short-Term Memory) model has addressed the issues existing in RNN when handling time-series signals.

Given the forecasting of multiple indicators, we decided that, unlike the first question where ARIMA model was used for forecasting, in this question we will use a sliding window mechanism to handle the time series input, combined with the memory units and gate control mechanism of the LSTM model, which can effectively capture patterns and trends in time series. Recursive prediction further extends the model's capabilities to generate forecasts for several years into the future. This method not only relies on historical data but also utilizes the correlation between multiple features to provide a more flexible and accurate forecasting solution.

The prediction process of sliding window method combined with LSTM model is shown in the following figure:

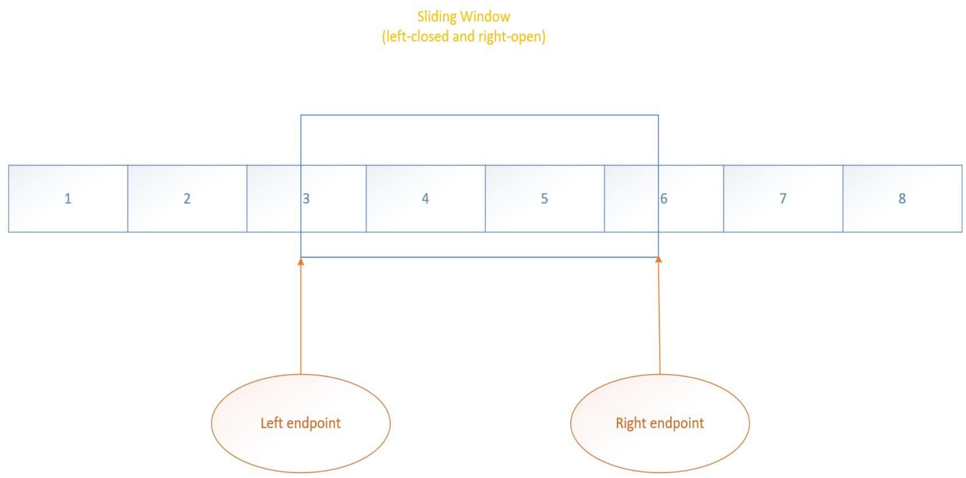

Figure 12. Sliding Window Method Flowchart

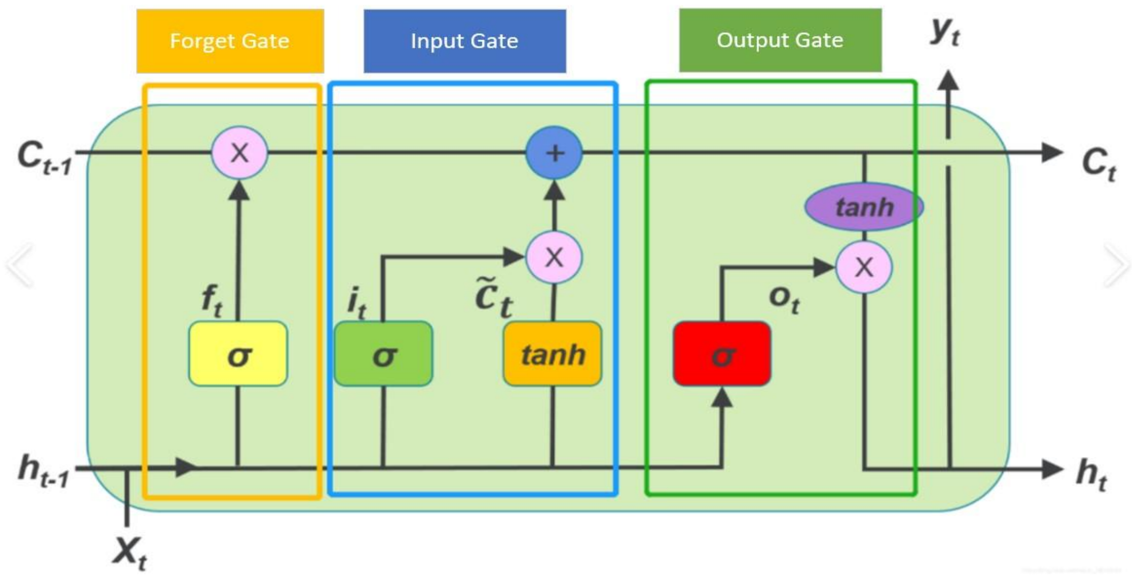

Figure 13. LSTM Model Diagram

The reason for our choice of using the sliding window method in combination with the LSTM model lies in the fact that the ARIMA model presumes that the variations in data are linear and stable. It demonstrates a relatively weak adaptability to complex non-linear patterns or circumstances where multiple potential influencing factors exist. The pet industry might exhibit a distinct upward trend, which fails to satisfy the stability requirements.

Furthermore, we utilized the sales of pet food from multiple countries for prediction. If the ARIMA model were employed, a series of tests would be necessary and the autoregressive order p and moving average order q, among other hyperparameters of the model, would have to be determined for each dataset. By adopting the sliding window method in conjunction with the LSTM model, not only can the process be simplified, but the LSTM model can also incorporate multiple feature variables. Simultaneously, the model is capable of learning the relationships among these features, thereby enabling more accurate prediction of global demand.

Additionally, the LSTM model employs a sliding window mechanism to dynamically update the input sequence for multi-step prediction. This process differs from that of the ARIMA model, which relies on static formulas. Instead, it generates dynamic predictions through the model's memory mechanism and historical data.

To conduct predictions using the sliding window method in combination with the LSTM model, the following steps can be adopted:

Step 1: Data standardization

In order to enhance the stability of model training, we scaled the data to the range of [0,1], using the following formula to achieve this:

$$X_{\text{scaled}} = \frac{X_{-}X_{\min}}{X_{\max -}X_{\min}} \tag{8}$$

Where:

X is the original data value.

$X_{\min}$ is the minimum value in the dataset.

$X_{\max}$is the maximum value in the dataset.

X_{scaled} is the normalized (scaled) value of X.

Step 2: Generate time series data

The creation of time series data is aimed at transforming historical data into a form that can be input into the LSTM model. In this task, it is necessary to convert the raw data into a sliding window structure, where each window encompasses the data of the past n time steps and predicts the value of the next time step. For time series $Y = \{y_1, y_2, \dots, y_4, \dots, y_N\}$.

We want to predict the value at time point T+1 based on the values at the first T time points. For a window size T and a sequence Y, the input data can be represented as:

$$X_t = \{y_{t-T}, y_{t-T+1}, \dots, y_{t-1}\} \tag{9}$$

Where X_t represents a data sequence from time step $t-T$to $t-1$ used for predicting the output y_t at time step t. The output is the value we hope to predict based on the input sequence X_t

Step 3: Model training

The LSTM model employs a specific gating mechanism to determine which information is to be retained, updated, or forgotten. The computational process of each LSTM unit involves the following components:

Input gate: Decides how much of the current input should be updated.

$$i_t = \sigma(W_t \cdot [h_{t-1}, x_t] + b_t) \tag{10}$$

Where, σ is the Sigmoid activation function, h_{t-1} is the output from the previous time step, x_t is the input at the current time step, $W_t$is the weight matrix, and b_t is the bias term.

Forget gate: Decides how much of the previous state information should be forgotten.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{11}$$

Where, f_t is the output of the forget gate, controlling the degree of forgetting of memory information in the LSTM unit.

Candidate memory unit: Decides the update value of the memory based on the current input.

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{12}$$

This step generates a candidate memory unit to supplement the memory in the LSTM.

Cell state update: Combines the forget gate and input gate to update the cell state.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \tag{13}$$

Where C_t is the current cell state, and C_{t-1} is the cell state from the previous time step.

Output gate: Decides the output of the current state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{14}$$

Where $o_t$is the output gate, controlling the activation values of the LSTM's output. Final output:

$$h_t = o_t \cdot \tanh(C_t) \tag{15}$$

Where $h_t$is the current output of the LSTM, which is used for calculations and predictions in the next time step.

Step 4: Predicting Future Data Dynamically

Using a sliding window mechanism, we construct an input sequence, using the feature matrix X and the target value y within a time window:

$$X = \begin{bmatrix} x_1, x_2, \dots, x_t \\ x_2, x_3, \dots, x_{t+1} \\ \vdots \\ x_{n-t}, x_{n-t+1}, \dots, x_{n-1} \end{bmatrix}, y = \begin{bmatrix} y_{t+1} \\ y_{t+2} \\ \vdots \\ y_n \end{bmatrix} \tag{16}$$

For each time window (x_t, x_{t-1}, x_{t-2}), the predicted target value y_t is:

$$y_t = f(x_{t-1}, x_{t-2}, x_{t-3}) \tag{17}$$

Use an LSTM model to predict the target value for the next year, $\hat{y}_{t+1}$. Connect the predicted value, $\hat{y}_{t+1}$, to the current time window and update it as the new input.

Step 5: Data restoration

During the inverse transformation, MinMaxScaler is applied to revert the data to its original scale. The formula is as follows:

$$X = X_{\text{scaled}} \cdot (X_{\max} - X_{\min}) + X_{\min} \tag{18}$$

Where:

X: The restored data, representing the actual predicted value.

X_{scaled}: The normalized value (in the range of 0 to 1) output by the model.

$X_{\min}$ and $X_{\max}$: The minimum and maximum values of the training data, used to map the normalized value back to the original range.

Step 6: Results Presentation

The figure below shows the projected sales of pet food in the US, France, Germany, and the global market over the next three years.

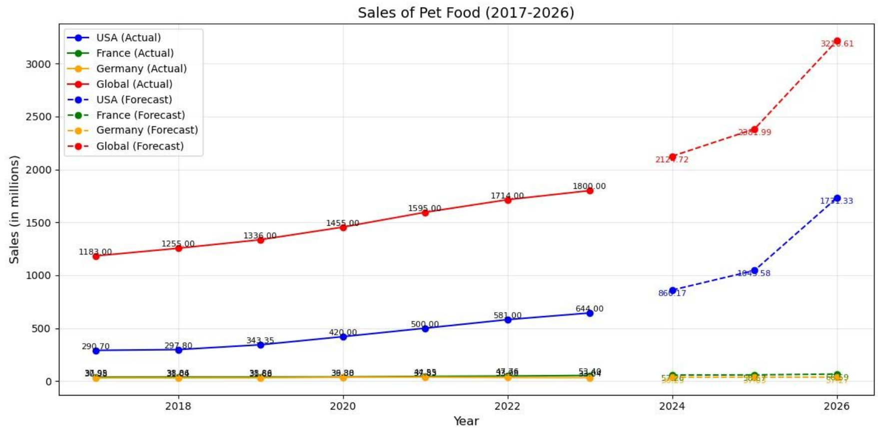

Figure 14. Forecast the global demand for pet food in the next three years

6. Model building and solution of question 3

Based on our understanding and analysis of the third question, we believe that the third question can be divided into two sub-questions: analyze the development of China's pet food industry; and predict its production and export of pet food in the next three years.

6.1. Analyze the development of China's pet food industry

Due to the limited data provided in the attachment, which only covers the Total Value of China's Pet Food Production and Total Value of China's Pet Food Exports from 2019 to 2023, we have collected additional data by conducting research and browsing various sources. This includes Total Value of China's Pet Food Production from 2016 to 2023, Total Value of China's Pet Food Exports from 2010 to 2023, and The scale of China's pet food industry and China's GDP from 2010 to 2023, which allows for a more comprehensive analysis of the development of China's pet food industry based on China's overall development.

From Problem 2, we can see that the trend of global demand for pet food is on an upward trend. Based on the trend of global pet food market demand and China's development, it is expected that the pet food industry in China will continue to maintain a rapid growth trend in the coming years. From the heat map, we can see that the pet food industry in China is expanding and developing continuously. And from the chart of GDP, we can see that the Chinese economy has been on the rise, which provides a solid foundation and broad development space for the pet food industry in China. This can also reflect the improvement of living standards, leading to an increase in pet-keeping families, so the market demand is huge. At the same time, it also drives the industrial upgrading and technological innovation, enhances the international competitiveness. The government's support is increasing, providing a guarantee for the industry development.

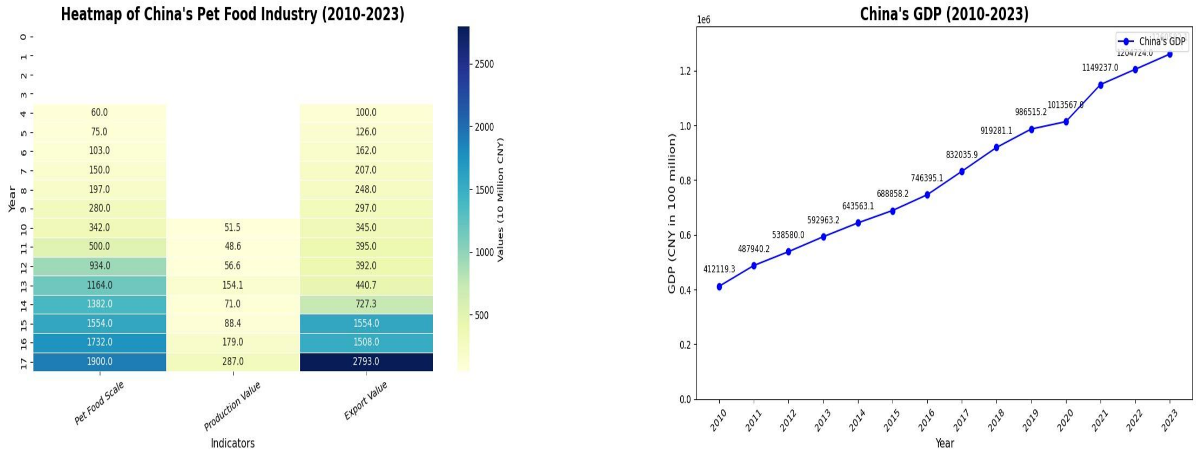

Figure 15. The heat map and line chart of China's pet food industry development and China's GDP

6.2. Predict the production and export of pet food

In order to predict the production and export of pet food, we still chose the LSTM model combined with the sliding window method to predict the next three years. The results are shown in the following figure:

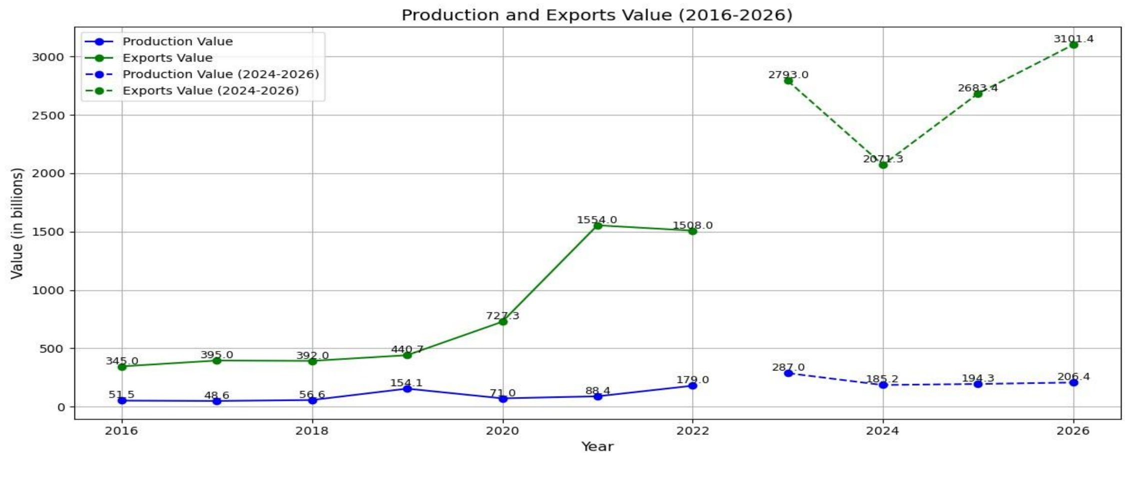

Figure 16. Forecast the production and export of pet food in the next three years

7. Model building and solution of question 4

Based on our understanding and analysis of Question 4, we believe that Question 4 can be divided into two sub-problems: make an appropriate mathematical model; develop feasible strategies for the sustainable development of China's pet food industry.

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7.1. Make an appropriate mathematical model

To investigate the influence of the new foreign economic policies of European countries and America on China's pet food industry, we collected monthly data on the export volume and export value of Retail packaged canned dog or cat food, Other retail packaged dog or cat food feeds, Manufactured feed additives, and Unlisted formulated animal feed from 2015 to 2023 from the official website of China Customs. We summed up these four indicators and regarded them as the export volume and export value of China's pet food, enabling a quantitative description of the research issue.

The following bar chart shows the collected data, and it is clear that there are several months with a significant decrease in both export volume and export value, which may be due to policies implemented by the US and Europe.

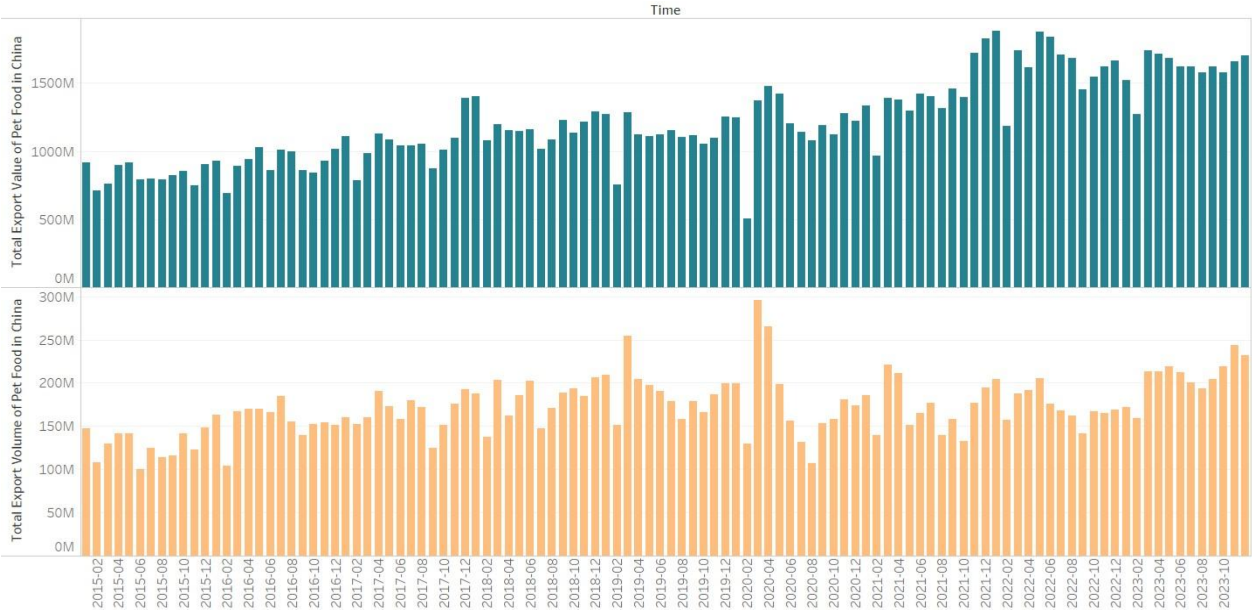

Figure 17. A bar chart showing export volume and export value.

We have collected some policies from 2015 to 2023.

Policy 1: EU Labeling Regulation Update (Jan 2018)

The European Union has adopted a new pet food labeling regulation, which requires imported pet food to comply with stricter labeling and ingredient requirements, aiming to enhance transparency and quality of pet food, which may have certain impact on China's pet food exports.

Policy 2: Phase One Trade Agreement (Feb 2020)

The agreement includes lifting China's ban on the import of pet food containing ruminant animal ingredients, and simplifying related testing requirements. This provides more opportunities for US pet food to enter the Chinese market, and may also lead to a decline in Chinese pet food exports.

Policy 3: USMCA (Jul 2020)

This agreement replaces the North American Free Trade Agreement and ensures zero tariffs on pet food trade between the United States, Canada, and Mexico. This enhances the competitiveness

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of North American pet food in the global market and counteracts the influence of Chinese pet food globally.

Policy 4: EU Organic Labeling Regulation (Dec 2023)

The EU has updated its organic labeling requirements for pet food, stipulating that the EU organic production logo can only be used if 95% of the agricultural ingredients in pet food are organic. This policy raises the certification standards for organic pet food and increases demand for pet food that meets environmental standards, which may have a certain impact on China's pet food exports.

The figure below shows the trend of export volume and export value with policy time points highlighted:

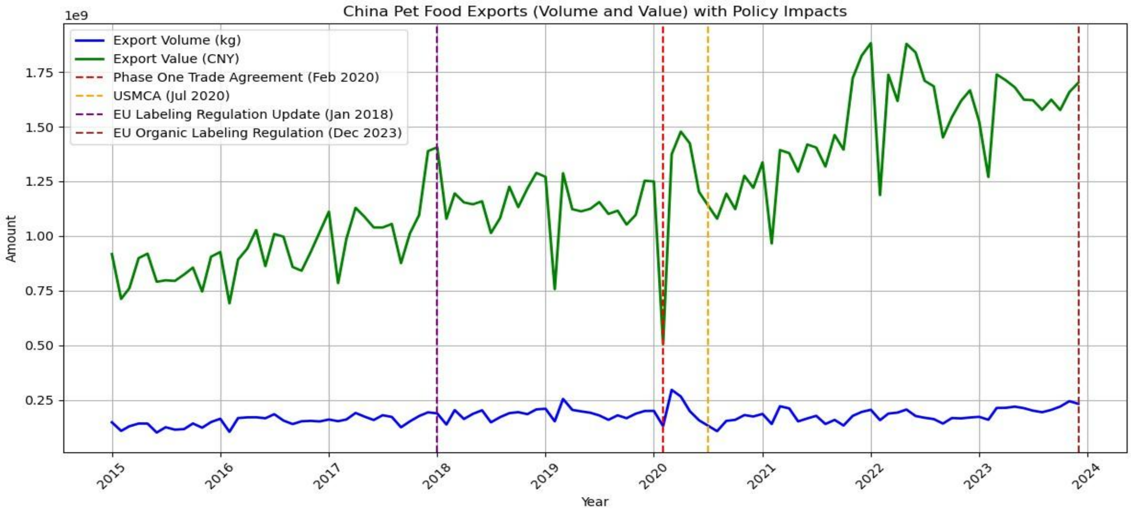

Figure 18. A line chart showing export volume and export value

To investigate whether these policies have had a significant impact on China's pet food industry, we decided to establish a DID model with Total Export Value of Pet Food in China as the dependent variable, reflecting the pet food industry in China.

Using a DID model to analyze the impact of foreign economic policies on China's pet food industry can effectively isolate the effects of policies from other external factors, control for time and individual differences, and reduce bias. By comparing changes before and after policy implementation, the DID model provides a clear causal inference, helping to quantify the specific impact of policy interventions and is particularly suitable for panel data analysis, which is simple and easy to interpret.

The mathematical form of the DID model can be expressed as:

$$\text{Export Value}_{it} = \alpha + \beta_1 \text{Post}_t + \beta_2 \text{Treated}_t + \beta_3 (\text{Post}_t \times \text{Treated}_t) + \epsilon_{it} \quad (19)$$

Where:

Export Value_{it}: The export value of pet food from China at time t.

$Post_t$: A dummy variable indicating the time after the policy implementation (1 if after, 0 otherwise).

Treated$_i$: A dummy variable indicating the treated group (China). It equals 0 before the policy implementation and 1 afterward.

$Post_t \times$ Treated_t: An interaction term representing the impact of the policy implementation on China's export value, capturing the marginal effect of the intervention.

ϵ_{it}: The error term capturing unobserved factors.

We aim to investigate the influence of four policies on the exports of pet food from China. Therefore, it is necessary to create dummy variables for each policy to indicate the variations in different time periods before and after the policy implementation, as follows:

Phase One Trade Agreement: This policy came into effect after February 2020. Therefore, the time is coded as 0 before February 2020 and 1 afterward.

USMCA: This policy came into effect after July 2020. Therefore, the time is coded as 0 before July 2020 and 1 afterward.

EU Labeling Regulation Update: This policy came into effect after January 2018. Therefore, the time is coded as 0 before January 2018 and 1 afterward.

EU Organic Labeling Regulation: This policy will come into effect after December 2023. Therefore, the time is coded as 0 before December 2023 and 1 afterward.

According to the DID model, the following results are shown in the table below:

Source	SS	df	MS			
				Number of obs	=	108
				F(3, 104)	=	59.98
Model	6.6050e+18	3	2.2017e+18	Prob > F	=	0.0000
Residual	3.8176e+18	104	3.6707e+16	R-squared	=	0.6337
				Adj R-squared	=	0.6232
Total	1.0423e+19	107	9.7407e+16	Root MSE	=	1.9e+08

Figure 19. The results of the DID model regression

The DID model results (F = 59.98, P ¡ 0.001) confirm that the policy variables significantly impact China's pet food exports. An adjusted R^2 of 0.6232 indicates that 63.32% of the export value variations are explained by these policies. This highlights the vital role of international policies in fostering industry growth and provides insights for refining export strategies.

7.2. Develop feasible strategie

Below are feasible strategies for the sustainable development of the pet food industry in China:

A.Expand International Market Share: According to the forecast in Question 3, China's pet food export value will continue to grow. As global market demand rises, Chinese companies should intensify efforts to expand their international market presence, leveraging free trade agreements and relevant policies to further increase export share.

B.Improve Product Quality and R&D Capabilities: As shown in the analysis in Question 4, foreign policies have a significant impact on China's pet food market. Therefore, Chinese companies should focus on improving food quality, especially in the organic and environmentally friendly pet food sector. Increased investment in R&D is crucial to ensuring that products meet international market standards and enhancing competitiveness.

C.Adapt to Global Policy Changes: Global economic policies, particularly tariff policies from Europe and the United States, have a notable impact on China's pet food exports. Companies should continuously monitor global policy trends, especially changes in tariff barriers and labeling regulations. Based on the findings of Question 4, strengthening policy alignment with countries like the U.S. and European nations is essential. Ensuring products meet international regulatory requirements and actively promoting internationalization and standardization of industry policies are key.

D.Optimize Domestic Market Development: While expanding into global markets, the domestic market also holds significant potential. The forecast in Question 1 shows that China's pet industry will maintain steady growth. Enterprises should focus on brand building and market promotion to increase consumer awareness of high-quality pet food, thereby enhancing market share and providing stable support for exports.

E.Sustainable Development and Environmental Strategy: As global attention to sustainability and environmental concerns increases, companies should integrate sustainable development principles into their production processes. This not only helps to enhance brand image but also facilitates obtaining more environmental certifications to meet the demands of international markets. At the same time, optimizing resource use and reducing carbon footprints will improve the overall competitiveness of enterprises.

F.Data-Driven Decision Making: Based on the DID model analysis from Question 4, companies can quantify the impact of various policies on exports and optimize decision-making through data-driven insights. This enables companies to make more precise strategies in global competition, allowing them to respond quickly to market changes.

8. Conclusion

8.1. Model Advantages

This study employed a comprehensive analytical framework using factor analysis, ARIMA, LSTM, and DID models. The factor analysis identified key drivers of industry growth by reducing data complexity. The ARIMA model effectively provided short-term forecasts of industry trends. The LSTM model, leveraging its advanced nonlinear capabilities, captured long-term demand fluctuations. Lastly, the DID model quantified the impact of trade policies on China's pet food exports, offering valuable insights for policy evaluation. Together, these models complement each other and enhance the reliability of the findings.

8.2 Discussion of Research Findings

The research confirmed that socio-demographic shifts and rising incomes are key drivers of China's pet industry, with the ARIMA model suggesting cyclical fluctuations in demand. The LSTM model projects long-term growth, highlighting the need for continued innovation. The DID model underscores the significant influence of trade policies on China's pet food exports. These findings support the study's core assumptions, though the potential for unforeseen regulatory changes remains a limitation.

8.3. Research Limitations

The study has some limitations, including the reliance on limited data for predicting pet industry trends, and the potential bias of using only a few representative countries. Additionally, the policy effects analyzed focused only on negative impacts, and the study began with data as recent as 2019, limiting long-term insights. Access to global pet data also posed challenges.

8.4. Future Research Directions

Future studies should expand the scope to include more pet species and integrate alternative data sources like social media sentiment. Hybrid AI models, such as Transformer-based architectures, could further enhance prediction accuracy. A more comprehensive analysis of policy effects, both positive and negative, would provide a balanced perspective. Cross-country studies could help better understand global market dynamics.

As the pet industry continues to evolve, data-driven insights will remain critical for shaping business strategies, informing policy decisions, and ensuring sustainable industry growth. By addressing existing research gaps and embracing emerging analytical methodologies, future studies can contribute to a more comprehensive and actionable understanding of the pet industry's trajectory.

Author contributions:

Conceptualization, J. K and D. L; methodology, J. K; software, J. K; validation, J. K., D. L and Q. W; formal analysis, D. L; investigation, D. L and Q. W; resources, J. K; data curation, D. L; writing—original draft preparation, J. K and D. L; writing—review and editing, J. K and D. L; visualization, J. K; supervision, J. K; project administration, J. K; funding acquisition, D. L and Q. W. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest:

The authors declare no conflict of interest.

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