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Based on machine learning: analysis, prediction, and strategy for the development trends of the pet industry and related industries

Jilong Wang[1*], Weidong Peng[2]

[1]School of Avionics and Electrical Engineering, Civil Aviation Flight University of China, Chengdu, China
[2]School of Aeronautical Engineering, Civil Aviation Flight University of China, Chengdu, China

*Corresponding Author. Email: 2522113605@qq.com

Abstract. Driven by consumption upgrading and sustained economic growth, the global pet industry has expanded rapidly. As a representative emerging market, China's pet economy has exceeded RMB 500 billion in scale; however, it faces challenges such as intensifying market competition, low export dependence, and fluctuations in international policies. This study employs a combination of the ARIMA time series model, Holt's linear trend method, Principal Component Analysis (PCA), and Ordinary Least Squares (OLS) regression to systematically examine the development trends of China's pet industry, the structural differentiation of the global pet food market, and China's production capacity and export potential in pet food. The findings indicate that China's pet industry is transitioning from a phase of rapid growth to a more mature stage characterized by moderated expansion. Over the next three years, the market size is projected to grow at an average annual rate of 10.5%, with the focus of competition shifting toward product differentiation and service upgrading. Global demand for pet food exhibits pronounced regional disparities: the U.S. market is approaching saturation, the European market maintains a competitive advantage in quality and safety, and emerging markets such as China are becoming the primary engines of growth. Although China's pet food production reached RMB 270.3 billion in 2023, exports accounted for less than 2%, highlighting a structural imbalance characterized by demand-driven domestic consumption and relatively weak international competitiveness. PCA results reveal that trade barriers and production costs are the primary factors constraining exports. Based on these quantitative findings, this study proposes strategies including short-term optimization of supply chain costs, long-term expansion into high-potential markets in Southeast Asia and Latin America, and the strengthening of digital marketing capabilities. These recommendations aim to provide data-driven decision support for the sustainable development of the industry and the enhancement of firms' international competitiveness.

Keywords: ARIMA model, quantitative models, Holt's linear trend method, PCA, OLS regression

1. Introduction

With the continuous improvement in living standards, the pet industry has risen rapidly on a global scale, becoming an increasingly significant component of the consumer market. According to the *Global Pet Market Report 2023*, the global pet industry has surpassed USD 300 billion in size, with a Compound Annual Growth Rate (CAGR) of 6.8%. This trend is driven by a combination of demographic shifts, accelerated urbanization, and the strengthening emotional bond between humans and their pets. In China in particular, the pet economy has experienced explosive growth: the market expanded from RMB 200 billion in 2019 to RMB 500 billion in 2023, while the penetration rate of pet-owning households increased from 17% to 25%. However, this rapid expansion has also brought structural challenges. Intensifying market competition, low export dependence resulting in limited international influence, and fluctuations in international trade policies have all increased operational risks for enterprises. Against this backdrop, how to employ quantitative analysis to uncover industry development trends, optimize resource allocation, and enhance international competitiveness has become a focal concern for both academia and industry [1].

Most existing studies focus primarily on qualitative analyses of pet consumption behavior or on localized characteristics of regional markets, while systematic quantitative research on global market dynamics, industrial chain synergies, and policy impacts remains insufficient. For instance, current literature generally overlooks the alignment between China's pet food export potential and global market demand, and fails to thoroughly examine the disruptive role of e-commerce channels in reshaping traditional trade models in the digital economy era. Furthermore, the impact mechanisms of international economic policies—such as tariff adjustments and trade barriers—on China's pet industry have yet to be rigorously quantified [2]. These research gaps constrain industry participants' ability to adapt to complex international environments and limit the scientific precision of policymaking.

In response, this paper takes China's pet industry as its core research object and constructs a multidimensional quantitative analytical framework by integrating the ARIMA time series model, Holt's linear trend method, Principal Component Analysis (PCA), and Ordinary Least Squares (OLS) regression. The study seeks to address the following key issues: (1) the internal logic and future trajectory of China's pet industry as it transitions from rapid growth to maturity; (2) the differentiated demand patterns in the global pet food market and their implications for Chinese enterprises; (3) pathways to overcoming bottlenecks in China's pet food production and exports; and (4) the quantitative effects of changes in international economic policies and corresponding adaptive strategies. By integrating historical data, market dynamics, and policy variables, this study not only reveals the stage-specific characteristics of China's pet industry and the evolving global competitive landscape, but also provides data-driven decision support for corporate strategic adjustment and policy optimization. Figure 1 illustrates the overall research framework and workflow of this study.

The contributions of this paper are threefold. First, by combining time series models with trend forecasting methods, it systematically characterizes the lifecycle evolution of China's pet industry, thereby addressing the lack of quantitative assessment of market maturity in existing research. Second, by incorporating differentiated demand across major global regions, it proposes targeted export strategies, offering new insights for overcoming the "low-end lock-in" dilemma in China's pet food sector. Third, it innovatively integrates principal component analysis with policy quantification models to reveal the inhibitory effects of key factors—such as trade barriers and production costs—on exports, providing empirical support for enterprise risk mitigation and policy formulation. The findings not only enrich the theoretical framework of pet industry economics but also offer practical guidance for the industry's sustainable development amid the dual forces of globalization and digitalization.

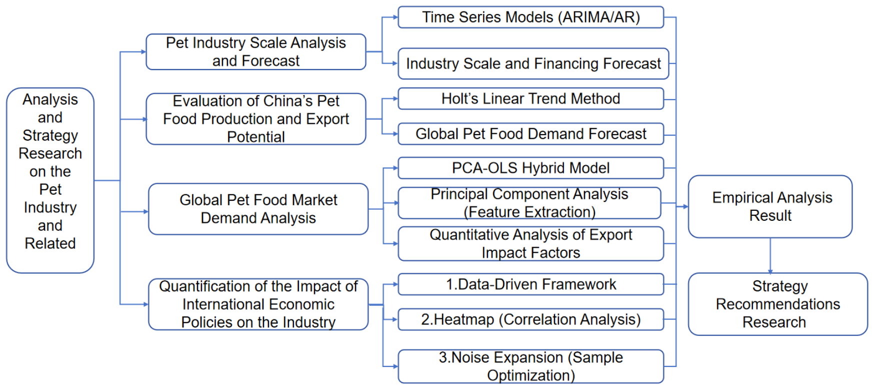

Figure 1. Research framework of this study

2. Forecasting analysis of the development of China's pet industry

2.1. Development status of China's pet industry

From a macro perspective, this section first examines the overall market of China's pet industry. Figure 2 illustrates the changes in industry scale across different years (2019–2023). The data indicate that, over this period, the total market size has continued to expand, although the growth rate has exhibited noticeable fluctuations. Specifically, there was a sharp decline in the growth rate between 2015 and 2016, followed by a significant rebound from 2016 to 2017. Between 2017 and 2020, the growth rate experienced mild fluctuations and eventually stabilized. From 2020 to 2023, however, the growth rate showed a gradual downward trend.

Regarding investment in the pet-related industry, Figure 3(a) shows the trend in the number of pet-related businesses, while Figure 3(b) depicts the number of financing cases in the pet market. An integrated analysis indicates that the overall number of pet-related businesses has been increasing, with growth flattening slightly between 2021 and 2022, followed by the fastest growth rate during 2022–2023. The number of financing cases in the pet market generally increased from 2014 to 2018, declined during 2018–2020, rebounded in 2020–2021, and stabilized between 2021 and 2023. The most rapid increases occurred in 2014–2015, while the steepest declines were seen in 2019–2020 [3].

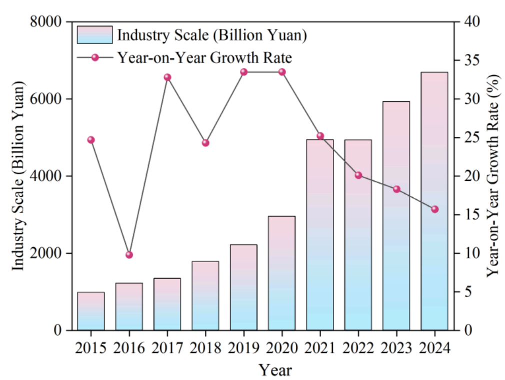

Figure 2. Market size and annual growth rate of China's pet industry (2015–2023)

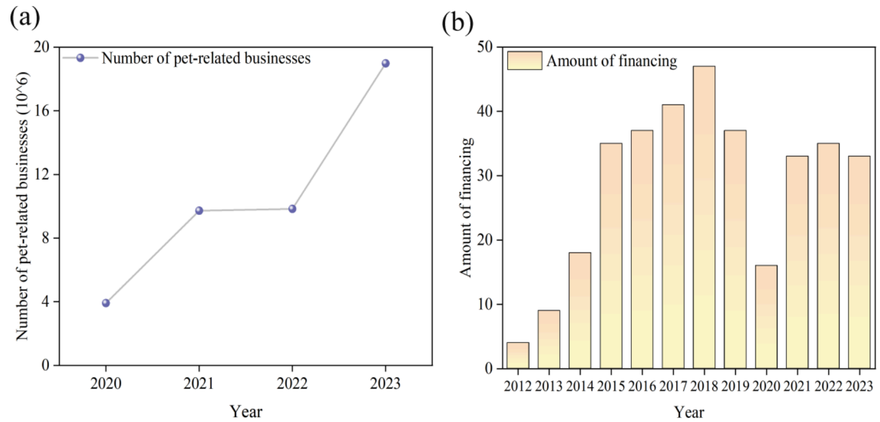

Figure 3. Development scale of China's pet-related industries and evolution of market investment and financing characteristics: (a) Historical trend of pet-related enterprises in China; (b) Historical investment activity in China's pet market

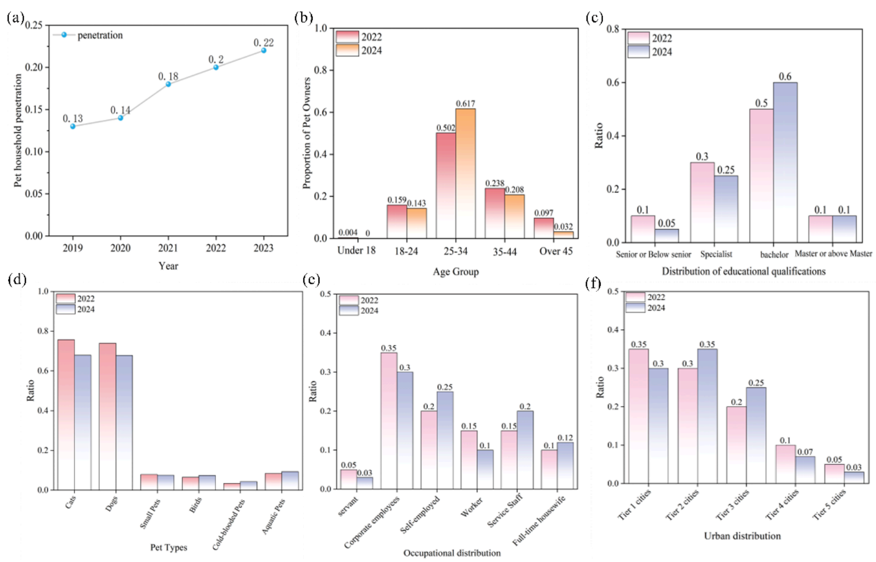

Figure 4. Changes in China's pet household penetration rate and analysis of pet owner characteristics: (a) Trends in pet household penetration rate; (b) Age distribution of pet owners; (c) Educational attainment distribution of pet owners; (d) Distribution of pet types; (e) Occupational distribution of pet owners; (f) Distribution by city tier of pet owners

To gain deeper insights into the factors driving the development of China's pet industry, a micro-level analysis was conducted. In recent years, pets have become increasingly popular among the population. From the perspective of household pet penetration in China, Figure 4(a) shows changes in pet household penetration rates across different years (2019–2022). The data indicate a consistent upward trend, with the growth rate during 2020–2021 notably higher than in other years, likely reflecting the increasing number of families treating pets as part of the household and the growing importance of pets in people's lives. Figure 4(b) illustrates the age distribution of pet owners, showing that younger individuals are particularly enthusiastic about keeping pets. Figure 4(c) displays the educational distribution of pet owners, highlighting the proportion of pet owners across different education levels in 2022 and 2024 [4]. Figure 4(d) covers six common types of pets, offering a broad view of market diversity and the relative popularity of each type. To further segment the pet-owning population, Figure 4(e) examines the impact of occupational distribution on pet ownership, while Figure 4(f) shows how the level of urban development indirectly affects the proportion of pet owners. Taken together, the analysis of the relationship between the proportion of pet owners and multiple factors in 2022 and 2024, combined with household penetration data, demonstrates that the demand for pets has increased substantially, driving the robust growth of the pet industry and its related sectors.

2.2. Construction of the forecasting model

Under conditions of relatively limited data availability, it is not feasible to directly rely on auxiliary variables from other pet-related sectors to predict the current state of the industry. Therefore, this study adopts time series forecasting models centered on autoregressive structures. Specifically, the ARIMA model is employed to forecast the scale of the pet industry and the number of investment and financing cases, while a simpler Autoregressive (AR) model is used for analyzing the time series of cat and dog populations due to their relatively short data spans. Time series analysis has been widely applied across various fields, including economics, meteorology, and biomedicine, where non-stationarity is a common challenge. As a classical and effective forecasting approach, the ARIMA model is capable of handling non-stationary data with complex characteristics such as trends, seasonality, and noise. By decomposing the ARIMA model into its Autoregressive (AR), Integrated (I), and Moving Average (MA) components, and examining its parameter estimation and forecasting mechanisms, the model's significance and practical value in time series analysis can be fully demonstrated, thereby providing robust support for industry forecasting and decision-making.

2.2.1. Autoregressive (AR) component

The autoregressive component constructs the model based on the historical values of the time series itself, aiming to capture the intrinsic relationship between the current value and its past observations. For the AR(p) process, the mathematical representation is given in Equation (1):

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_p y_{t-p} + \varepsilon_t \tag{1}$$

Here, denotes the value of the time series at time, $\phi_1, \phi_2, \cdot\cdot\cdot, \phi_p$ represents the autoregressive coefficients, $y_{t-1}, y_{t-2}, \cdot\cdot\cdot, y_{t-p}$ corresponds to historical observations, and is a white noise sequence with zero mean and constant variance, following an independent and identically distributed (i.i.d.) process. For example, when analyzing pet market sales data, if the current month's sales exhibit a linear relationship with those of previous months, the AR component can effectively model this dependence.

2.2.2. Integrated (I) component

To address non-stationarity, differencing plays a crucial role. The fundamental idea is to eliminate trend components by computing differences between adjacent observations, thereby transforming a non-stationary series into a stationary one. The order of differencing determines the number of differencing operations applied. The first-order difference is defined in Equation (2):

$$\Delta y_t = y_t - y_{t-1} \tag{2}$$

and the second-order difference is defined in Equation (3):

$$\Delta^2 y_t = \Delta y - \Delta y_{t-1} = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2})) = y_t - 2y_{t-1} + y_{t-2} \tag{3}$$

In practical applications, the time series is typically examined first, and in most cases, first-order differencing $d = 1$ is sufficient to achieve stationarity. For instance, the market size of the pet industry often exhibits an upward trend over time; applying first-order differencing yields the year-to-year growth increments, which can then be modeled more effectively.

2.2.3. Moving Average (MA) component

The moving average component focuses on capturing the relationship between the current value of the time series and past forecast errors. The MA(q) model is expressed mathematically in Equation (4):

$$yt = \mu + \varepsilon_t + +\theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots \theta_q\varepsilon_{t-q} \tag{4}$$

In this formulation, μ denotes the mean of the series, $\theta_1, \theta_2 \cdots \theta_q$ represents the moving average coefficients, and $\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-q}$ refers to past white noise terms. For example, in forecasting demand for pet products, if previous prediction errors influence current demand, the MA component can incorporate such effects into the model.

By integrating the AR, I, and MA components, the complete ARIMA(p, d, q) model is obtained, as shown in Equation (5):

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_P B^P)(1 - B)^d y_t = (1 + \theta_1 B + \theta_2 B^2 + \cdots \phi_q B^q)\varepsilon_t \tag{5}$$

Here, B denotes the lag operator, and the differencing operation is represented $By_t = y_{t-1}$, $(1 - B)^d y_t$ accordingly.

2.2.4. Parameter estimation of the ARIMA model

Parameter estimation is a critical step in constructing the ARIMA model. Common methods include Maximum Likelihood Estimation (MLE) and the least squares method. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) serve as important diagnostic tools. The ACF is primarily used to determine the order q of the MA component. By examining the decay pattern of autocorrelation coefficients, an initial estimate of q can be obtained. The PACF, on the other hand, is used to determine the order p of the AR component, as its truncation behavior provides key guidance for selecting p [5]. For example, if the ACF rapidly approaches zero after lag q, it may indicate an MA(q) process; similarly, if the PACF cuts off after lag p, this suggests an AR(p) process.

2.2.5. Forecasting principle of the ARIMA model

Forecasting with the ARIMA model is based on known historical data and estimated parameters. For a future time point $t + h$, the forecast value is given by Equation (6):

$$y_{t+h} = \mu + \phi_1 y_{t+h-1} + \phi_w y_{t+h-2} + \cdots + \phi_p y_{t+h-p} + \varepsilon_{t+h} + \theta_1\varepsilon_{t+h-1} + \theta_2\varepsilon_{t+h-2} + \cdots + \theta_q\varepsilon_{t+h-q} \tag{6}$$

In practical applications, the appropriate values of (p), (d), and (q) are first determined using historical data, followed by parameter estimation. The known data are then substituted into the forecasting equation, and future values are obtained iteratively. For example, when forecasting investment and financing activities in the pet industry over the next few quarters, an ARIMA model can be constructed based on historical data and used to generate forward-looking estimates, thereby informing investment decisions.

2.2.6. Holt's linear trend method

Holt's linear trend method is an extension of exponential smoothing, specifically designed to handle data with linear trends. Its core idea is to combine the level and trend components of the original time series, enabling it to capture and forecast linear changes effectively. Let the time series be y_t . The basic model is defined in Equation (7):

$$Lt = \alpha y_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$
$$Tt = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \tag{7}$$

where L_t represents the level estimate at time (t), T_t denotes the trend estimate, and α and β are smoothing parameters ranging from 0 to 1. The parameter α controls the weight assigned to current observations, while β determines the sensitivity to changes in the trend.

The smoothing parameters are typically determined using optimization techniques such as the least squares method, by minimizing a measure of forecast error (e.g., mean squared error). Once the parameters y_{t+h} are estimated, the forecast for a future time point $(t+h)$ can be computed using Equation (8):

$$y_{t+h} = L_t + hT_t \tag{8}$$

That is, the forecast value at a future time is obtained by adding h times the trend estimate T_t to the current level estimate L_t.

2.3. Analysis of forecasting results

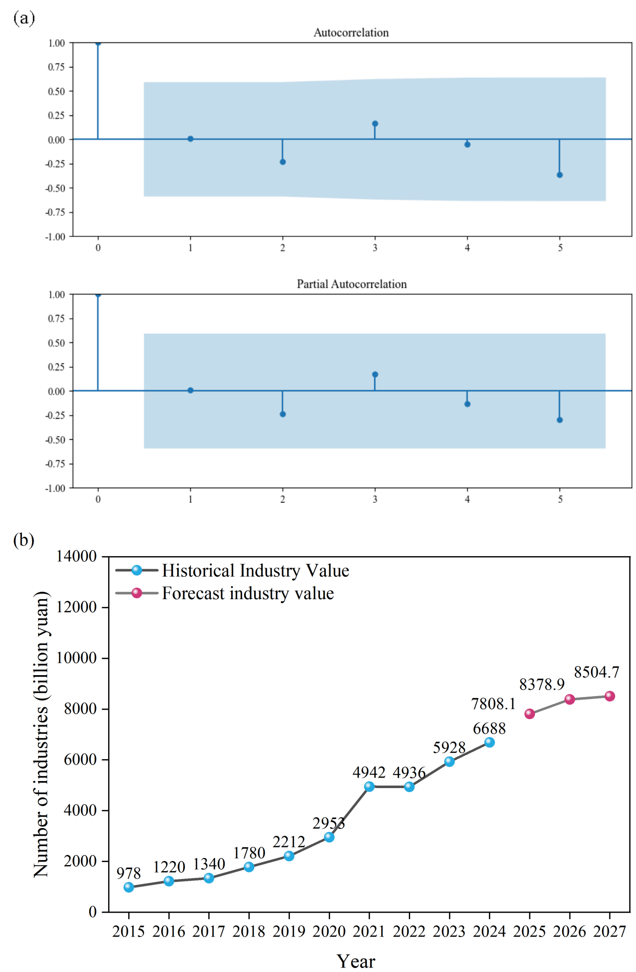

Figure 5. Historical evolution and trend forecast of China's pet industry scale: (a) Parameter identification of the forecasting model; (b) Forecast of industry scale

Using the ARIMA model described above, this study conducts a comprehensive and detailed analysis and forecasting of multiple time series dimensions within China's pet industry. The final results are presented in the form of intuitive graphical visualizations. For the prediction of China's pet industry scale, an ARIMA model is employed. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are shown in Figure 5(a). The selected model parameters are $(p,d,q) = (1,1,1)$, and the time series demonstrates a satisfactory stationary fit.

A closer examination of Figure 5(b) reveals both historical patterns and future projections. From 2015 to 2024, the scale of China's pet industry exhibits steady growth, with a relatively high average annual growth rate. After 2020, influenced by the broader pandemic environment and shifts in consumption behavior, the growth rate initially increased and then declined, possibly due to the heightened role of pets as companions during lockdown periods. From the forecast for 2025 to 2027, the industry is expected to continue expanding, albeit at a slower pace, gradually entering a mature stage. Market saturation is likely to increase, leading to intensified competition.

In addition, the forecasting results for investment and financing cases in China's pet industry are presented in Figure 6. Figure 6(a) shows the ACF and PACF plots of the model, where the optimal parameters are again identified as (1, 1, 1), indicating a good stationary fit.

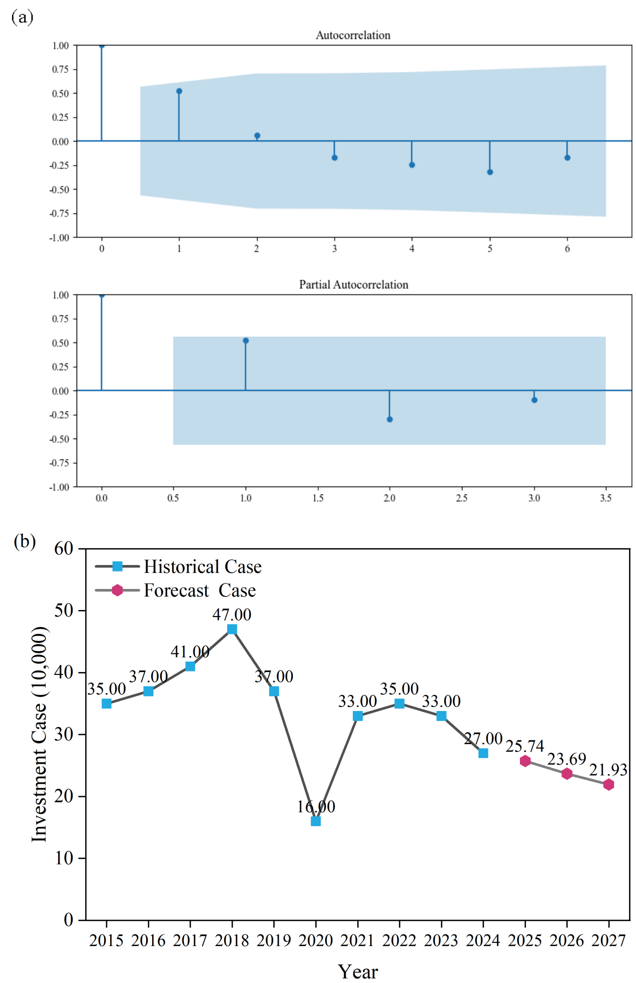

Figure 6. Historical evolution and trend forecast of investment cases in China's pet industry: (a) Model parameter identification; (b) Forecast of investment cases

An analysis of Figure 6(b) provides insights into both historical and future investment trends. From 2012 to 2018, investment enthusiasm in the pet industry increased significantly, with the number of financing events rising rapidly and peaking in 2018, followed by a decline. In 2020, the number of financing cases dropped sharply due to the impact of the pandemic. Looking ahead to 2025–2027, the number of financing events is expected to decrease. This trend may reflect the industry's transition into a more rational development phase, where investors apply stricter criteria in selecting high-return projects. As market saturation increases, capital

—driven by profit-seeking behavior—tends to reassess risk and return profiles [6]. From a policy perspective, it is essential to support innovation among Small and Medium-sized Enterprises (SMEs), for example through tax incentives and other supportive measures to enhance competitiveness. At the same time, establishing robust project evaluation and screening mechanisms can guide capital toward high-quality investments, thereby promoting the sustainable development and structural upgrading of the pet industry.

The following presents the results obtained using Holt's linear trend method for forecasting the populations of pet cats and dogs in China.

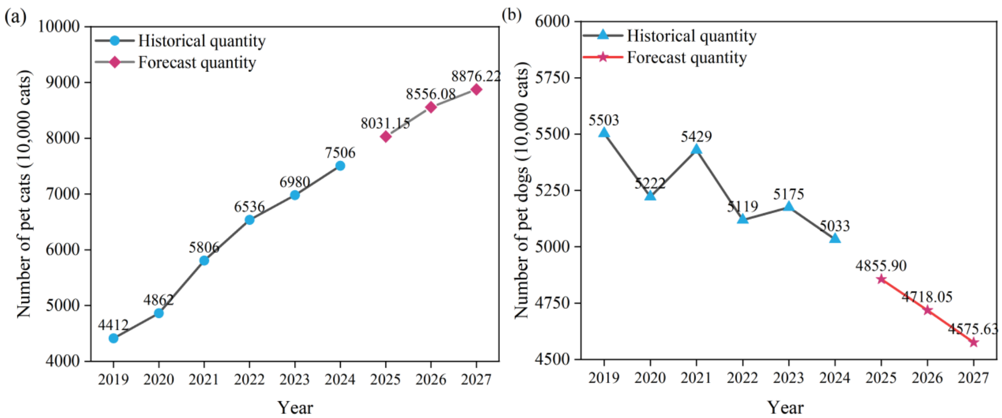

Figure 7. Trends and forecasts of pet cat and dog populations in China: (a) Forecast of pet cat population; (b) Forecast of pet dog population

The analysis of Figure 7(a) shows that the pet cat market experienced rapid growth from 2019 to 2023, with a growth rate significantly exceeding that of other pet categories. This expansion is largely attributable to economic development and the proliferation of the internet, which have facilitated consumption and information dissemination. Forecast results indicate that the market will continue to expand significantly from 2025 to 2027, making it a key growth driver within the industry. Several factors may contribute to this trend: the relative convenience of cat ownership, which aligns well with urban living conditions; the rising cultural preference for cats among urban residents, amplified by social media influence; and the development of high-end pet food and pet product markets, driven by increasing consumer concern for pet health and quality of life. In contrast, the forecast results for the pet dog market in Figure 7(b) indicate that from 2019 to 2023, the market exhibited considerable fluctuations and relatively slow overall growth, with signs of saturation. This is primarily due to the stabilization of ownership levels and the higher costs associated with dog ownership, which constrain further expansion. From 2025 to 2026, the market is expected to experience a slight decline, influenced by intensified competition, stable demand, and increasingly stringent urban dog ownership regulations. From a strategic standpoint, enterprises should explore new growth opportunities, such as developing specialized health-oriented pet food tailored to different life stages and health conditions of dogs; expanding veterinary and care services, including preventive healthcare and rehabilitation; and investing in pet behavioral training services to improve pet management and owner experience. These measures can help overcome current constraints and support sustained industry development [7].

In summary, the overall scale of China's pet industry is expected to continue growing over the next three years, albeit at a slower rate. This reflects increasing market saturation as well as changes in the macroeconomic environment and consumption structure. Nevertheless, the industry retains considerable resilience and growth potential, particularly in meeting emotional needs and promoting synergies across the industrial chain. Structural differentiation within the market is becoming more pronounced. The pet cat segment, driven by convenience, evolving pet ownership culture, and the expansion of high-end product markets, is expected to maintain strong growth and serve as a core engine of industry development, fostering diversification and refinement. In contrast, the pet dog market, constrained by higher ownership costs and regulatory factors, is projected to remain stable or experience slight contraction between 2025 and 2027, necessitating the exploration of new business models and opportunities. In terms of investment and financing, the industry has transitioned from an early-stage "blue ocean" characterized by high investment enthusiasm to a more rational development phase. Future financing volumes are expected to decline, with investors placing greater emphasis on project quality and profitability. Capital allocation will become more optimized, facilitating industry consolidation and upgrading. Overall, the pet industry is currently at a critical stage of transformation. Enterprises must closely monitor market dynamics, strengthen innovation capabilities, and enhance risk management to ensure sustainable growth. Meanwhile, policymakers should adjust regulatory frameworks in line with evolving conditions to promote standardized and healthy industry development, enabling the sector to fully realize its economic and social value [8].

3. Analysis of market demand in pet-related industries

3.1. Characteristics of regional markets

In 2023, the global pet food market reached a scale of USD 1.2 trillion, with pronounced regional disparities. As shown in Figure 8, the United States ranks first with USD 57,384.6 million in revenue, attributable to its large pet ownership base, high household consumption levels, and a well-established pet industry. China follows with USD 7,420.0 million, benefiting from the rapid expansion of its pet market, ongoing consumption upgrading, and substantial latent demand derived from its large population. The United Kingdom ranks third with USD 7,224.6 million, supported by its strong pet culture and advanced economic development [9]. Brazil, with USD 6,288.0 million, ranks fourth, driven by relatively high pet ownership rates and the expansion of the middle class in this emerging economy. Countries such as Germany, France, and Japan also generate considerable revenue, though at gradually decreasing levels. This is largely due to their advanced economies, which enhance residents' purchasing power for pet-related consumption, and the prevalence of pet culture, which elevates the status of pets within households and stimulates market growth. Overall, pet food market revenues across countries are closely associated with economic development, pet culture, and pet ownership rates. As the global pet market continues to expand, these national markets are expected to maintain steady growth.

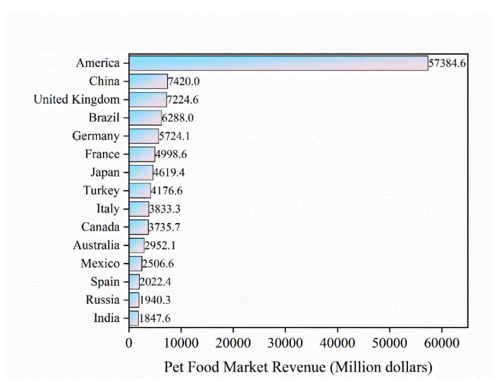

Figure 8. Global pet food market revenue

To further examine the pet food industry, this study conducts a more detailed analysis of market size changes in four major regions—the United States, the European Union, Japan, and China—as illustrated in Figure 9. From 2017 to 2022, all four regions exhibited consistent growth trends. The U.S. market expanded rapidly from approximately USD 300 billion to USD 700 billion, driven by a deeply rooted pet culture, stable economic conditions supporting high consumption levels, and continuous innovation in products and services. The EU market grew steadily from around USD 200 billion to USD 250 billion, benefiting from high pet ownership rates, relatively stable economic conditions, and strict animal welfare regulations that encourage sustained investment. Japan's market increased from approximately USD 100 billion to USD 150 billion, reflecting steady growth influenced by population aging, which has increased demand for companionship, as well as the rising status of pets and ongoing industry development. China's market experienced the most rapid expansion, surging from about USD 100 billion to USD 500 billion, driven by urbanization, a sharp increase in pet ownership, consumption upgrading, and the rapid development of the industry. In general, the growth across these regions is shaped by factors such as pet culture, economic conditions, demographic structures, consumption patterns, and industry development, and is expected to continue expanding in the future. Pet food prices constitute a critical factor influencing the pet market. Based on the above data, a comparative visualization of pet food market values across the four major regions is provided [10].

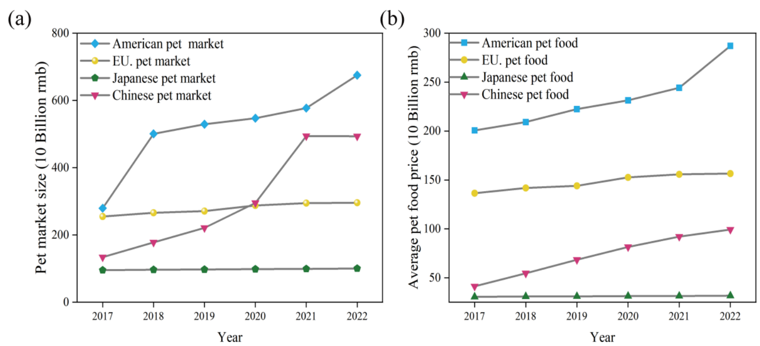

Figure 9. Comparative analysis of pet market size and pet food market value in major regions: (a) Market size of four major regions; (b) Pet food market value in four major regions

As shown in Figure 9, from 2017 to 2022, pet food market values across the four regions exhibit distinct trends. In the United States, the market increased from approximately USD 200 billion to USD 270 billion, driven by demand for high-quality products, heightened awareness of pet health, and potential inflationary effects. The EU market remained relatively stable at around USD 150 billion, reflecting a mature market structure, balanced competition, and stringent regulatory frameworks. In Japan, the market rose gradually from approximately RMB 50 billion to RMB 60 billion, influenced by factors such as an aging pet population, increasing humanization of pets, and the relatively smaller market size. In China, the market value grew significantly from around RMB 50 billion to RMB 100 billion, propelled by consumption upgrading, market expansion, and increasing brand development. To further explore the relationship between pet food market value and overall pet market size, a correlation analysis is conducted across the four regions, as shown in Figure 10.

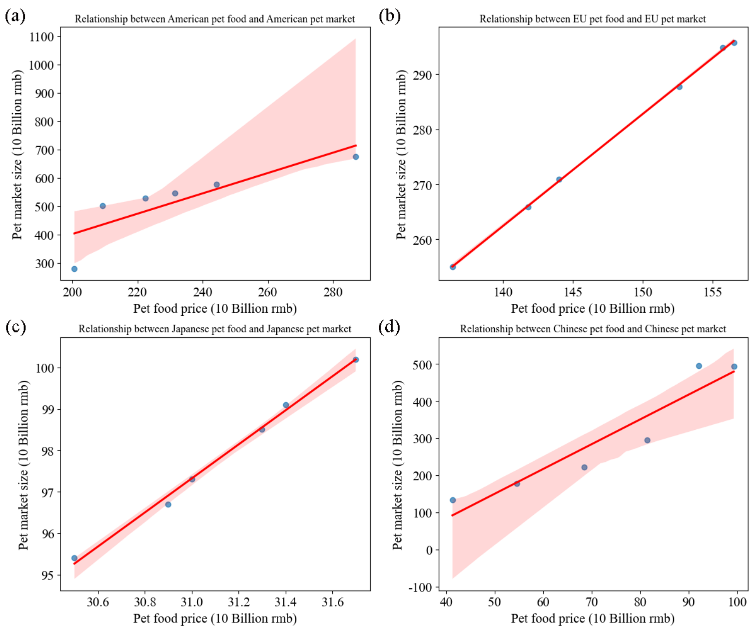

Figure 10. Correlation analysis between pet market size and pet food market value in major regions: (a) United States; (b) European Union; (c) Japan; (d) China

The results indicate a generally positive correlation between pet food market value and overall pet market size. The strength of this correlation varies across regions, influenced by factors such as local consumption patterns, pet culture, market maturity, and animal welfare regulations. Overall, as the value of the pet food market increases, the overall scale of the pet market tends to expand correspondingly [11].

3.2. Forecasting analysis of the pet food industry

Similarly, Holt's linear trend method is employed to forecast the pet market value and pet food demand across the four major regions, following the same principles outlined earlier. As shown in Figure 11, both the overall pet market and the pet food market in these regions exhibit clear upward trends, and the forecast results continue to indicate sustained growth. Driven by factors such as pet culture, economic conditions, demographic structure, consumption patterns, and industry development, growth in China and the United States is particularly prominent. The forecasting results align well with observed trends, reflecting the ongoing evolution of the global pet market structure. As the industry becomes more comprehensive and interconnected, there is an increasing need for robust, data-driven strategic planning to support decision-making.

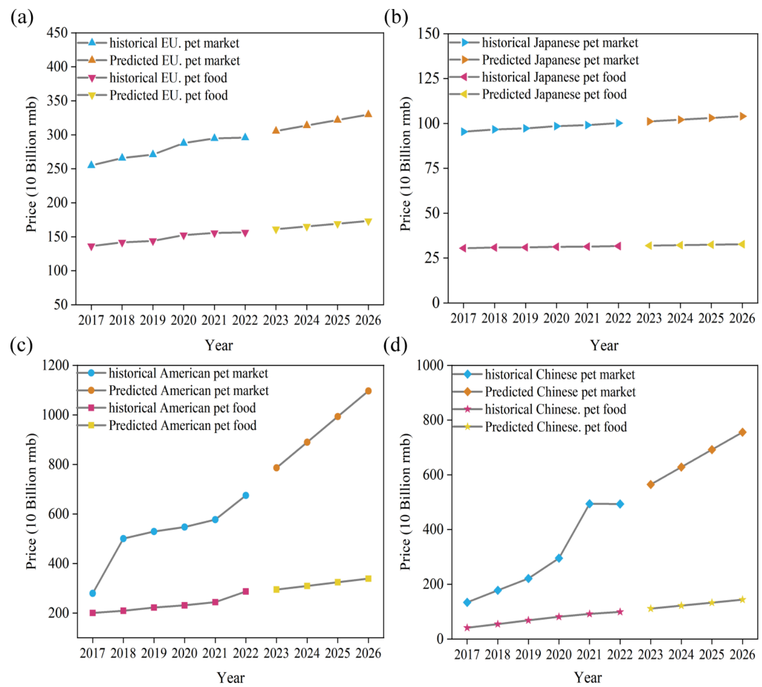

Figure 11. Forecast of evolutionary trends in pet markets and pet food submarkets in major countries (regions): (a) European Union; (b) Japan; (c) United States; (d) China

In summary, the U.S. market is approaching saturation and is likely to rely on consumption upgrading among existing pet owners for future growth. In contrast, European markets are gradually unlocking their growth potential. From a strategic perspective, the U.S. market should focus on enhancing consumption among existing pet owners through innovative products and services, while European markets should expand product lines and promote sustainable business models. At the global level, increased investment in Europe and strengthened brand competitiveness will be essential for capturing high-end market share and meeting the rising demand associated with growing pet populations.

3.3. Production and export potential of China's pet food industry

Building on the forecasting models discussed earlier, this study further projects the total production value and export value of China's pet food industry over the next three years and presents the results through visualization. As shown in Figure 12, China's pet food industry has experienced rapid expansion, with total production value surging from RMB 44.07 billion in 2019 to RMB 270.3 billion in 2023, demonstrating a remarkably strong growth trajectory. According to the forecast, by 2026, the industry's production value is expected to rise further, reaching approximately RMB 500 billion [12].

In terms of exports, China's pet food export value declined to a low point in 2020 but has since shown a gradual recovery, reaching RMB 2.9 billion in 2023. Based on current trends, export value is expected to maintain a steady growth trajectory over the next three years.

Overall, the continuous expansion of domestic demand for pet food has significantly driven the rapid growth of production capacity. Although export activity is also growing steadily, its scale remains relatively small compared to the substantial domestic production volume, indicating a structural imbalance between domestic demand and international market penetration.

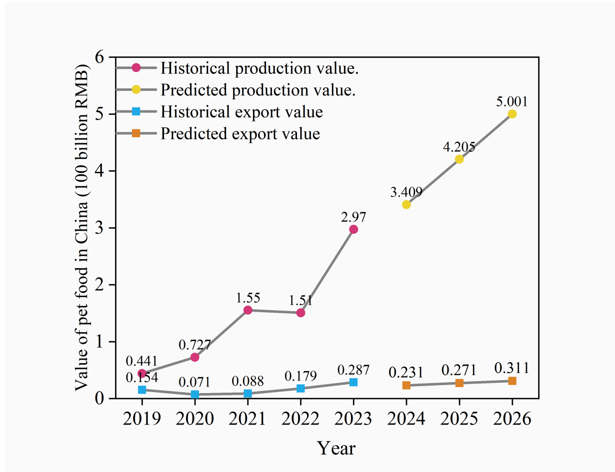

Figure 12. Forecast of production and export values of China's pet food industry

4. Analysis of industry driving factors based on PCA–OLS

By integrating collected data on European and American external economic policies with the previously compiled datasets, and in reference to the forecasting results of the pet industry, this study examines the relationships between China's pet food production and export volumes and a range of influencing factors. These two variables—production volume and export volume—are taken as core indicators representing China's pet food industry, while the explanatory variables include both domestic and international industry development conditions as well as foreign economic policies affecting the sector [13]. As illustrated in Figure 13, a correlation heatmap is employed to quantify the degree of interdependence among various features.

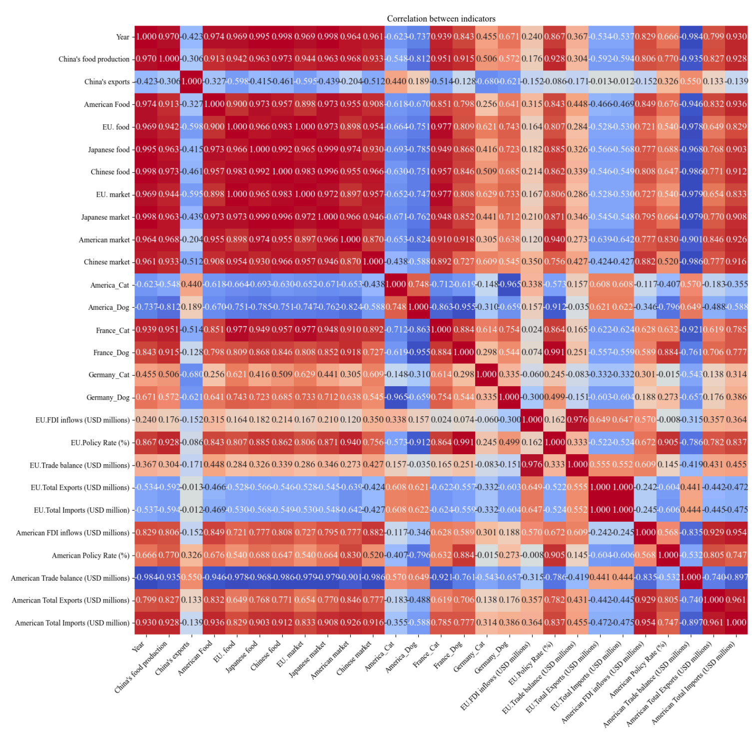

Figure 13. Correlation heatmap of key features

The results indicate that, within China's pet food industry, production scale exhibits a strong correlation with both domestic market demand and export value. The robust growth of domestic demand constitutes the primary driver of production expansion. Although export value shows a rising trend, its scale remains relatively limited compared to the vast domestic market, suggesting that its potential has yet to be fully realized.

Building upon the analysis of inter-feature correlations, the study further investigates the relationships between China's pet food production and exports and other influencing variables. Given the large number of variables and relatively limited sample size, Principal Component Analysis (PCA) is applied for dimensionality reduction. More than 20 original features are reduced to six principal components. The effectiveness of PCA is evaluated using cumulative variance contribution rates and the factor scores of each principal component. To clearly illustrate the contribution of individual features to each principal component, two heatmaps are employed to present the detailed results. Principal Component Analysis (PCA) is a widely used technique in multivariate data analysis. Its fundamental principle lies in performing eigenvalue decomposition on the covariance matrix of the original dataset to construct a new set of orthogonal principal components. These components are ordered according to the proportion of variance they explain, with the first principal component accounting for the largest share, followed by subsequent components in decreasing order. In practical applications, dimensionality reduction is achieved by retaining only a few principal components with high variance contribution rates, thereby effectively simplifying high-dimensional data structures.

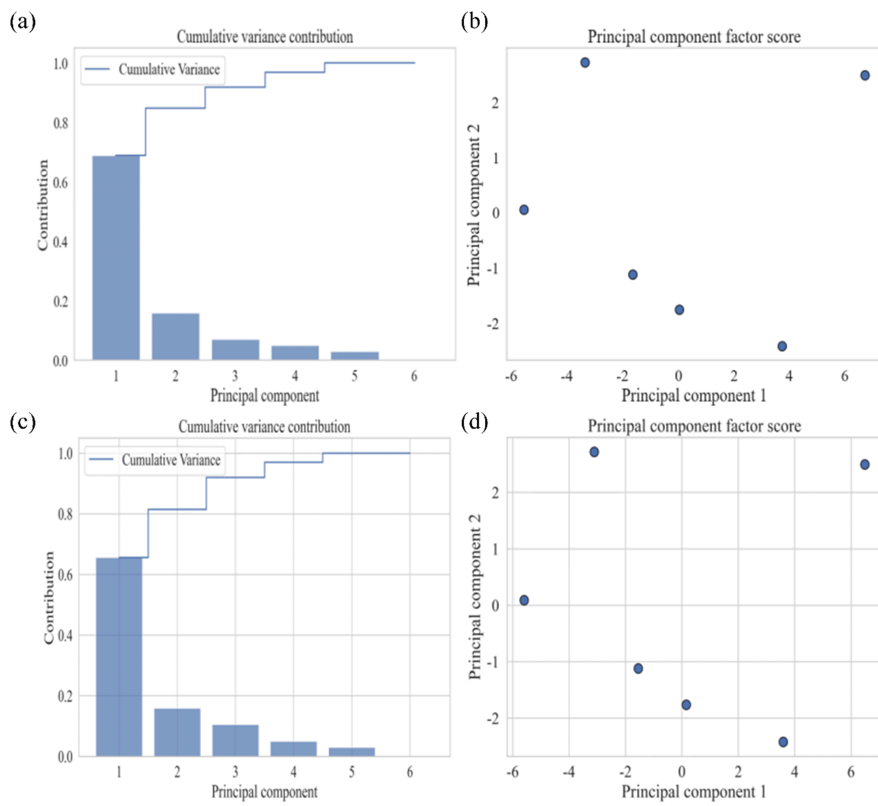

Figure 14. Principal component analysis results of features related to China's pet food export scale and production value: (a) Cumulative variance contribution after dimensionality reduction for export volume; (b) Principal component loadings for export volume; (c) Cumulative variance contribution after dimensionality reduction for production value; (d) Principal component loadings for production value

As shown in Figure 14, the first six principal components explain more than 95% of the total variance, indicating an effective dimensionality reduction with substantially reduced redundancy. The first principal component has the strongest explanatory power, with a contribution rate exceeding 60%, integrating information from multiple features, while the variance contribution of subsequent components decreases progressively. The first and second principal components are primarily used to distinguish the distribution of samples; their score distributions are relatively uniform, with no evident deviations, suggesting that the extraction is stable and reliable. The loading matrix further indicates that the first principal component incorporates information from the first nine features, which contribute significantly to it, whereas the sixth principal component is driven by a limited number of features and plays a unique role in explaining specific data patterns.

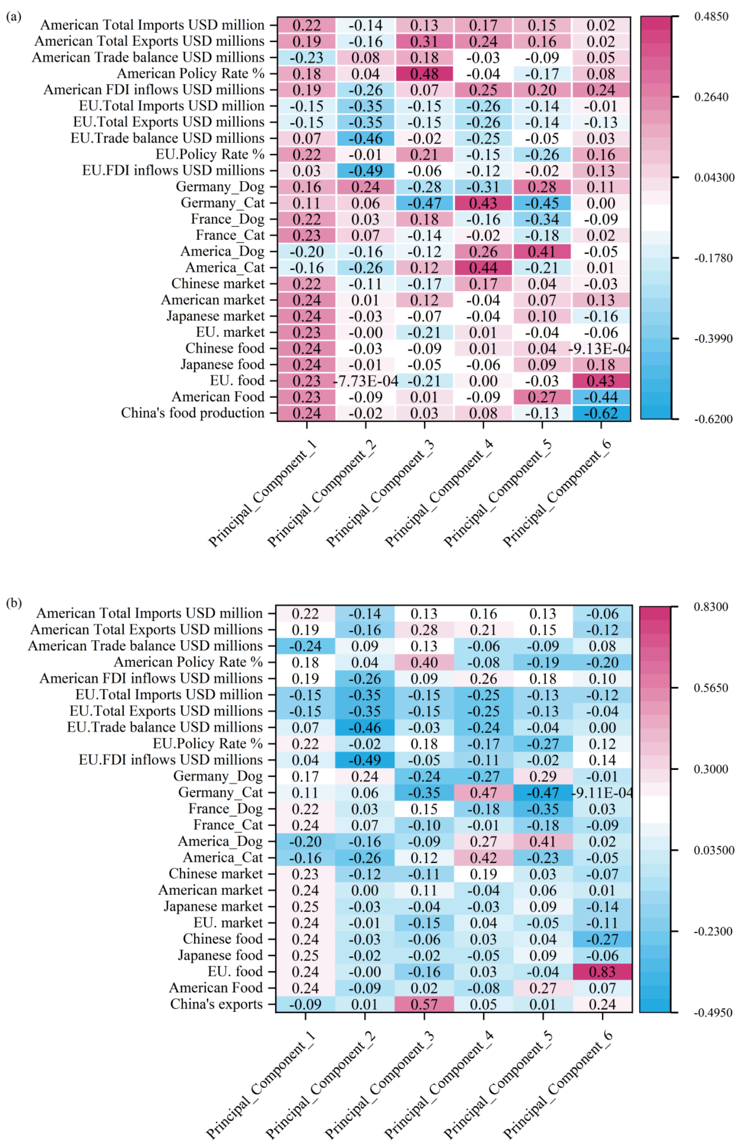

Figure 15. Further illustrates the relationships between principal components and original features. Panel (a) Shows the heatmap of correlations between the principal components and original features for China's pet food export volume, while panel (b) Presents the corresponding heatmap for total production value

As illustrated in Figure 15, panel (a) presents the principal component loading matrix obtained after applying PCA to the factors influencing China's pet food export volume, while panel (b) shows the corresponding loading matrix for China's total pet food production value. Each element in these matrices represents the correlation (loading) between an original feature and a principal component. By analyzing the magnitude and sign of these loadings, one can assess the importance of each feature within a principal component and its direction of influence. To provide a more intuitive representation, heatmaps are employed, where color intensity reflects the magnitude of the loadings.

Ordinary Least Squares (OLS) is a widely used linear regression method in statistics and econometrics. Its primary objective is to fit the data by minimizing the sum of squared residuals—that is, the differences between observed and predicted values. In essence, it identifies a line (or a hyperplane in multivariate settings) that minimizes the sum of squared vertical distances from all data points. By constructing two OLS regression models with the principal components as explanatory variables, the impacts of these components on China's pet food industry can be quantified. This enables the identification of key composite driving factors (as represented by the principal components), clarifies their quantitative relationships with production and export performance, and provides a basis for evaluating model reliability and applicability, thereby supporting production decisions and forecasting [14].

Table 1. OLS regression results for the principal components of China's pet food exports

OLS Regression Results						
Dep. Variable	y	Log - Likelihood	-4.4698			
R quared	1.000	No. Observations	36			
Model	OLS	AIC	22.94			
Adj.R squared	1.000	Df Residuals	29			
Method	Least Squares	BIC	34.02			
F statistic	1.450e+05	Df Model	6			
Date	Sun, 24 Nov 2024	Covariance Type	nonrobust			
Prob (F statistic)	1.55e-63	Time	10:36:18			
	coef	std err	t	$p > \|t\|$	[0.025	0.975]
const	48.0934	0.058	827.498	0.000	47.975	48.212
x1	- 4.1854	0.012	- 361.789	0.000	-4.209	-4.162
x2	0.1187	0.026	4.558	0.000	0.065	0.172
x3	34.2939	0.047	736.595	0.000	34.199	34.389
x4	5.7941	0.061	94.231	0.000	5.668	5.920
x5	1.2219	0.073	16.764	0.000	1.073	1.371
x6	3.4190	5.661	0.604	0.551	-8.159	14.997
Omnibus		2.57	Prob (Omnibus)			0.280
Durbin-Watson		1.765	Jarque-Bera (JB)			1.509
Skew		0.464	Prob (JB)			0.470

Given the limited sample size, the regression model may suffer from instability when applied directly. To address this issue, Gaussian noise is introduced to augment the dataset, thereby significantly increasing the sample size. Although this approach may reduce the goodness of fit, it enables the model to yield more reasonable and stable results. The significance analysis indicates that, except for the sixth principal component, all other components have statistically significant effects on export volume.

Regarding China's pet food exports, as shown in Table 1, Principal Component Analysis (PCA) was used to reduce the dimensionality of all features to six relevant components. A regression analysis was then conducted using the least squares estimation method to establish a model of the relationship between China's pet food exports and these six principal components. This model allows us to identify which principal components (i.e., composite factors of the original features) have a significant impact on export volume, as well as the extent and direction of that impact.

The R-squared (coefficient of determination) and Adj. R-squared (adjusted coefficient of determination) from the OLS regression results can be used to assess the model's fit to the data. It can be seen that R-squared is close to 1, indicating that the model has a strong explanatory power for China's pet food export volume.

The F-statistic and its corresponding Prob (F-statistic) can be used to assess the overall significance of the model. If the Prob (F-statistic) value is small (typically less than 0.05), it indicates that the model is statistically significant as a whole, meaning that at least one principal component has a significant impact on export volume.

Examine the coefficients (coef), standard errors (std err), t-values, and *p*-values ($p > |t|$) for each principal component. If the *p*-value for a principal component is less than 0.05, it indicates that the component has a significant impact on China's pet food export volume. As can be seen, the *p*-value for Principal Component 6 is far greater than 0.05, indicating a weak relationship between the two.

Table 2. OLS regression results for the principal components of China's total pet food production value

OLS Regression Results						
Dep. Variable	y	Log - Likelihood	6.9921			
R quared	1.000	No. Observations	36			
Model	OLS	AIC	0.01586			
Adj.R squared	1.000	Df Residuals	29			
Method	Least Squares	BIC	11.10			
F statistic	1.450e+05	Df Model	6			
Date	Sun, 24 Nov 2024	Covariance Type	nonrobust			
Prob (F statistic)	9.45e-69	Time	11:36:18			
	coef	std err	t	$p > \|t\|$	[0.025	0.975]
const	48.0125	0.040	1,195.511	0.000	47.930	48.095
x1	-4.5974	0.009	-508.101	0.000	-4.616	-4.579
x2	0.3149	0.021	14.698	0.000	0.271	0.359
x3	28.1479	0.022	1,274.228	0.000	28.103	28.193
x4	2.2089	0.035	62.706	0.000	2.137	2.281
x5	0.5839	0.054	10.771	0.000	0.473	0.695
x6	-8.3855	4.658	-1.800	0.082	-17.911	1.140
Omnibus		0.395	Prob (Omnibus)			0.821
Durbin-Watson		2.258	Jarque-Bera (JB)			0.556
Skew		0.136	Prob (JB):			0.757

Regarding China's pet food production volume, as shown in Table 2, Principal Component Analysis (PCA) was used to reduce the dimensionality of all features to six relevant components. A regression analysis was then conducted using the least squares estimation method to establish a relationship model between China's pet food export volume and these six principal components. These six principal components are linear combinations of the original features and are capable of retaining the variance information of the original data to the greatest extent.

The R-squared (coefficient of determination) and Adj. R-squared (adjusted coefficient of determination) from the OLS regression results can be used to assess the model's fit to the data. It can be seen that R-squared is close to 1, indicating that the model has a strong explanatory power for China's pet food export volume.

The F-statistic and its corresponding Prob (F-statistic) can be used to assess the overall significance of the model. If the Prob (F-statistic) value is small (typically less than 0.05), it indicates that the model as a whole is significant, meaning that at least one principal component has a significant effect on export volume.

Examine the coefficients (coef), standard errors (std err), t-values, and p-values ($p > |t|$). If the p-value for a particular principal component is less than 0.05, it indicates that the component has a significant impact on China's pet food export volume. It can be seen that the p-value for Principal Component 6 is 0.082, which is far greater than 0.05, indicating a weak relationship between the two. Similar to the findings regarding China's pet food export volume, this suggests that the model aligns well with reality and effectively reflects the global development status of China's food industry.

5. Conclusion and outlook

5.1. Research conclusion

This study employs multidimensional quantitative methods to reveal the stage characteristics and core driving mechanisms of China's pet food industry. Forecasts based on ARIMA and Holt's linear trend models indicate that the Chinese pet industry has transitioned from a period of rapid growth to a mature stage with slowing growth. Over the next three years, the market is expected to expand at an average annual rate of 10.5%, with competition increasingly focused on product differentiation and service quality. Globally, the pet food market exhibits significant regional differentiation: the U.S. and European markets are approaching saturation, while emerging markets such as China and Brazil are becoming key growth engines. Although China's pet food production scale has expanded rapidly (with a 2023 output value of 270.3 billion RMB), exports account for less than 2%, highlighting a structural imbalance driven by domestic demand and limited international competitiveness.

Using PCA for dimensionality reduction and OLS regression models enhanced by data augmentation, the study further quantifies the influence of industry driving factors. In the domestic market, consumption upgrades and increased household pet penetration are the core drivers of production expansion; principal component 1—which integrates domestic market size, consumption habits, and related features—explains 60% of the variance in production. In terms of pet-related industry exports, international economic policies (trade barriers, tariff adjustments) and production costs serve as the key negative loadings in principal components 2–5, constraining export potential. By combining PCA for handling high-dimensional small-sample data with Gaussian noise to enhance data robustness, the constructed dual OLS regression models (for export volume and production value) achieved R^2 values close to 1, with principal components 1–5 showing significant effects on the dependent variables ($p < 0.05$), validating the methodology.

5.2. Practical implications

Based on these findings, a phased strategic approach is proposed. In the short term, measures should focus on optimizing supply chain costs (raw material procurement, technological upgrades), increasing policy responsiveness (dynamic adjustment of export layouts), and enhancing added value (development of functional foods and value-added services). For long-term planning, leveraging e-commerce channels to expand international brand influence (through digital marketing and cross-border platform operations), deepening engagement in high-potential markets (Southeast Asia, Latin America) to diversify risks, and promoting industry standardization to address international trade barriers are recommended [15].

5.3. Outlook

Future research can expand the model by incorporating additional regional policy variables (e.g., carbon emission regulations, animal welfare standards) and enterprise-level microdata to enhance explanatory power. Introducing dynamic panel models or machine learning algorithms could capture nonlinear relationships and time-lag effects. Cross-disciplinary studies that integrate consumer behavior and supply chain management theories may further explore the interactions between the pet economy and socio-cultural evolution [16].

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