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An Exploratory Analysis of Chinese Listed Fishery Companies' Competitiveness Based on Financial Indicators: A PCA Approach

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ABSTRACT

This paper is based on the financial data of Chinese listed fishery companies from 2018 to 2024, and constructs an indicator system that includes five dimensions: profitability capacity, operational capacity, capital structure, growth capability, and debt repayment capacity. Principal component analysis is used to evaluate their comprehensive competitiveness. The results show that the overall competitiveness of listed fishery companies is weak and volatile. When external shocks occur, the competitiveness of companies generally shows a significant decline, and the industrial support policies introduced by the government can improve the capital structure of companies and increase profitability in the short term. Further analysis reveals that insufficient growth capacity is the main weakness that constrains the long-term development of the industry, reflecting a lack of endogenous motivation within the company. In response to the above issues, this paper proposes the following policy recommendations: firstly, increase support for fishery technology innovation, focusing on key areas such as deep-sea aquaculture, intelligent equipment, and deep processing of aquatic products; Secondly, establish and improve the fishery risk warning and emergency response mechanism, and enhance the ability of companies to respond to emergencies; The third is to optimize fiscal subsidies and financial support methods, tilt more resources towards companies with high growth potential and sustainable operating capabilities, guide the industry to shift from scale expansion to quality improvement, and systematically enhance the comprehensive competitiveness of Chinese fishery companies.

Keywords: Financial Performance; Fishery Economy; Capital Structure Optimization; Industrial Resilience

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1. Introduction

The Chinese fishery industry holds a central position in the global seafood supply system, playing a strategic and irreplaceable role in national food security, coastal regional economic development, and the sustainability of marine ecosystems [1,2]. In recent years, the industry has faced complex external pressures, including the escalation of international trade barriers, sudden public health emergencies, and major environmental risk events, which collectively create a highly uncertain and rapidly evolving operating environment [3]. Listed fishery companies, as key drivers of industrial development, confront unprecedented challenges to the stability and sustainability of their competitiveness.

The evaluation of company competitiveness in existing literature often has limitations in capturing the vertical evolution of companies, especially in industries with high external volatility. Although cross-sectional analysis or static financial indicators are still common [4], they essentially overlook the temporal changes that influence performance trajectories, such as policy-driven adjustments and environmental shocks. This is particularly problematic for fisheries companies, where production cycles, resource availability, and supply chain dependencies can create path-dependent vulnerabilities that will manifest over a long period of time. Relying on a single point assessment may distort risk exposure and adaptability. Therefore, establishing an evaluation framework that reflects the trajectory of changes in competitiveness is crucial for accurately identifying industry risks and resilience characteristics [5].

In terms of dimensional structure, existing evaluations often oversimplify the complexity of company competitiveness. Competitiveness is fundamentally a composite system encompassing profitability capacity, operational capability, capital structure, growth capability, and debt repayment capacity [5,6]. For certain industries, more indicators may need to be considered. However, many studies tend to choose representative individual indicators as alternative indicators or treat different dimensions separately. This method fails to reflect the overall performance of the company in multiple dimensions, and it is difficult to determine how a serious weakness in one dimension affects overall competitiveness. For highly sensitive fishery companies, neglecting the integrity of multidimensional structures can lead to misjudgments about systemic risks.

This paper aims to develop a multidimensional competitive evaluation framework based on financial indicators for the fisheries industry. The goal is to accurately describe the comprehensive level and temporal evolution of the competitiveness of Chinese fishery listed companies. This framework utilizes principal component analysis (PCA) to integrate multiple dimensions while retaining the original indicator information, achieving comparative tracking of multidimensional capabilities. It provides quantifiable insights for identifying sources of industry vulnerability and comparing competitive differences between companies. This work helps to improve the evaluation methods for the competitiveness of agricultural and fishery companies, providing scientific decision support for enhancing the resilience of China's fishery sector and ensuring food security.

2. Theoretical Foundation and Literature Review

Company competitiveness is a system composed of multiple capabilities working together. Its core dimensions typically include profitability capacity, operational capability, capital structure, growth capability, and debt repayment capacity. The Resource-Based View (RBV) provides a foundational theoretical lens for understanding this multidimensional construct, emphasizing that sustained competitive advantage stems from a firm's internal bundle of heterogeneous resources and capabilities [7]. Falciola et al. [5] further conceptualize competitiveness as a multidimensional framework, arguing that the balance and coordination among these dimensions are essential for maintaining long-term advantage. However, in the fishery sector, which is highly resource dependent, this multidimensional equilibrium is particularly fragile, and systemic deficiencies are most evident in terms of growth capacity.

The growth trajectory of fishery companies faces multiple structural constraints. Their development largely depends on the right to use marine space and biological resources, which have strong public interest characteristics and are subject to strict regulation. Unlike crop farming or livestock husbandry, growth can usually be achieved through land expansion or herd size, and fishery companies cannot easily replicate operations to achieve scale. Instead, growth depends on strategies such as moving into offshore or deep-sea operations, developing high-value-added products, or extending along the value chain, all of which require significant technological barriers and capital intensity [8]. Second, fishery assets are typically highly specialized with high sunk costs, leading companies to adopt conservative investment behaviors under uncertainty. This asset-intensive and inflexible situation often leads to companies contracting rather than expanding after external shocks, thereby limiting long-term growth momentum. Third, persistent external disturbances further exacerbate these growth challenges. Brander et al. [1] pointed out that climate change forces global fisheries to require significant upfront research and development investment for adaptive transformation. Similarly, Quezada-Escalona et al. [3] find that fishery managers tend to favor short-term coping measures over long-term strategic investments in response to shifting resource distributions. In addition, incidents such as Japan discharging nuclear wastewater into the ocean can cause market losses for fishery companies and may weaken consumer confidence in seafood in the long run, damaging the foundation of brand building and market development [9,10]. Overall, these factors have led to long-term weakness in the core growth drivers—capital accumulation, technological innovation, and market expansion. In contrast, other agricultural subsectors face relatively fewer extreme and persistent negative shocks, allowing for more stable growth trajectories. Thus, the systemic deficiency in growth capability is not merely an idiosyncratic managerial issue but a structural bottleneck rooted in the interplay between the intrinsic attributes of the fishery industry and its external environment. Based on this theoretical reasoning, the first hypothesis is proposed:

Hypothesis 1. *Insufficient growth capability constitutes a systemic bottleneck constraining the development of China's listed fishery companies.*

Although a multidimensional perspective elucidates the composition of competitiveness, Dynamic Capabilities Theory offers a critical lens for understanding its evolution in turbulent environments. This theory suggests that a company's true competitive advantage lies not only in having valuable resources, but more importantly, in its ability to integrate and reconfigure internal and external capabilities to adapt to rapidly changing conditions [11,12]. For fishery companies operating under highly uncertain conditions, this dynamic adaptability is essential.

The current approach to competitiveness assessment shows significant limitations in terms of the time dimension. A large amount of research relies on cross-sectional data or single-period financial indicators, providing only a snapshot view and being unable to capture the evolutionary process of adaptive responses of companies over a continuous period of time [13]. Fishing operations are usually cyclical, characterized by high asset specificity and deep dependence on external conditions, rendering their value creation highly susceptible to both natural variability and shifts in international market sentiment [14,15]. Therefore, for fishery companies, competitiveness is not a fixed attribute, but a time trajectory formed by the interaction of external shocks and internal adjustments. Assessing competitiveness based solely on financial performance at a single point in time risks overlooking pre-existing vulnerabilities and may lead to misjudgments about the sector's overall risk profile. Empirical evidence suggests that, compared with relatively closed agricultural subsectors such as crop or livestock production, fishery companies exhibit significantly higher financial volatility due to their deeper integration into global value chains and direct exposure to marine ecological constraints [16]. This volatility manifests as fluctuations in short-term profits and a systematic decrease in long-term competitiveness. The frequent demand for crisis management consumes a significant amount of management attention and financial resources, limiting the company's ability to sustain investment in technological upgrades and market development, exacerbating the negative feedback loop between high volatility, low accumulation, and weak growth. In light of this theoretical and empirical rationale, the second hypothesis is formulated:

Hypothesis 2. *The competitiveness of China's listed fishery companies exhibits significantly higher volatility and* *a lower overall level compared to companies in other agricultural subsectors.*

From a methodological perspective, Principal Component Analysis (PCA) provides an effective solution to the previously proposed problem. PCA reduces dimensionality while maintaining the information content of the original multivariate indicator system, generating a small number of irrelevant principal components, thus enabling comprehensive evaluation of complex systems. This technology has been successfully applied in different fields of competitiveness research. For instance, Zhao et al.[17] employed PCA to evaluate urban competitiveness across 35 major Chinese cities; Xue and Yang[18] used it to evaluate regional logistics competitiveness. At the company level, Liu and Zhang[19] and Tang and Fu[20] applied similar methods to analyze the financial competitiveness of listed companies in specific industries. Lv and Abdul Salam[21] further demonstrated the effectiveness of data-mining-enhanced PCA models in evaluating innovation-driven enterprises. These studies collectively validate the advantages of PCA in handling high-dimensional, interrelated indicator systems. Based on this method and related theoretical foundations, this paper constructs a multidimensional competitiveness framework specifically for listed fishery companies to overcome the shortcomings of existing evaluations.

In summary, although prior literature has made progress in assessing agricultural companies' competitiveness[16], analyzing the impacts of external shocks[10], and refining evaluation methodologies[17], few studies have systematically integrated a multidimensional structural perspective with a comparative analysis of listed fishery companies. By constructing a multidimensional comparative framework, this paper aims to bridge this critical research gap and provide a scientific basis for a deeper understanding of Chinese listed fishery companies. The comparative method of this study can identify differences in competitiveness between companies and emphasize how weaknesses in specific dimensions lead to overall competitiveness risks.

3. Data and Methods

3.1. Data Sources

This paper utilizes the RESSET Financial Research Database and employs SPSS 27.0 and Origin 2024 for data analysis and graphical representation. Due to data availability, we selected financial data from Chinese listed agricultural companies spanning 2018 to 2024. Given the limited number of listed fishery companies, we have also added two other industry-listed companies with significant fisheries operations as fishery companies for processing. After excluding samples with severe missing data, a total of 322 company-year observations were obtained from 46 listed agricultural companies. This sample comprises 56 company-year observations from 8 listed fishery companies and 266 firm-year observations from 38 listed companies in agriculture, forestry, and animal husbandry.

3.2. Construction of the Index System

Based on the characteristics of listed companies and referring to a large number of existing references[13,22–24], following the principles of scientificity and feasibility in constructing an evaluation index system for company competitiveness, 13 secondary indicators were selected as the evaluation criteria for the competitiveness of Chinese agricultural listed companies, including profitability capability (including Return onEquity, Return on Total Assets, Sales Net Profit Margin, and Operating Profit Margin), operational capability (including Inventory Turnover Rate, Current Asset Turnover Rate, and Total Asset Turnover Rate), capital structure (Debt-to-Asset Ratio and Equity Multiplier), growth capability (Total Asset Growth Rate and Monetary Fund Growth Rate), and debt repayment capacity (Current Ratio and Quick Ratio). The indicators are detailed in **Table 1**.

Table 1. Competitiveness Index System of Agricultural Companies.

Primary Indicator	Secondary Indicator	Index	Measurement
Profitability Capacity	Return on Equity	X1	Net Profit/Average Net Assets
	Return on Total Assets	X2	Earnings Before Interest and Taxes (EBIT)/Average Total Assets
	Sales Net Profit Margin	X3	Net Profit/Operating Revenue
	Operating Profit Margin	X4	Operating Profit/Operating Revenue

Table 1. *Cont.*

Primary Indicator	Secondary Indicator	Index	Measurement
Operational Capacity	Inventory Turnover Rate	X5	Cost of Goods Sold/Average Inventory
	Current Asset Turnover Rate	X6	Operating Revenue/Average Current Assets
	Total Asset Turnover Rate	X7	Operating Revenue/Average Total Assets
Capital Structure	Debt-to-Asset Ratio	X8	Total Liabilities/Total Assets
	Equity Multiplier	X9	Total Assets/Shareholders' Equity
Growth Capacity	Total Asset Growth Rate	X10	Increase in Total Assets for the Year/Initial Total Assets
	Monetary Fund Growth Rate	X11	Increase in Monetary Funds for the Year/Initial Monetary Funds
Debt Repayment Capacity	Current Ratio	X12	Total Current Assets/Total Current Liabilities
	Quick Ratio	X13	Quick Assets/Total Current Liabilities

3.3. Methods

3.3.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is an analysis method that converts multiple variables into a few key components with nonlinear correlations through dimensionality reduction. In practical problems, when the research involves multiple variables and these variables are highly correlated, principal component analysis can be used for processing [25–27]. The specific analysis steps are as follows:

Positive Transformation Processing

Among the 13 indicators selected in this paper, some are moderate indicators. These indicators do not measure performance based on the absolute size of their values. They include the current ratio, quick ratio, debt-to-asset ratio, and equity multiplier; therefore, these indicators require positive transformation processing [28,29]. The specific operation involves standardizing the selected moderate indicators using the following formula. In this paper, a general standard value of 2 is chosen for the current ratio, 1 for the quick ratio, 50% for the debt-to-asset ratio, and 2 for the equity multiplier [28].

$$X^T = \frac{1}{|X_i - A|} \tag{1}$$

In this equation, X^T represents the data after positive transformation of the corresponding indicator, without altering its essence. X_i denotes the original value of the data, and A is the general standard value of the indicator.

Z-Score Standardization

Since different indicators use various measurement methods, it is necessary to standardize all data before proceeding to the next step. The main objective of Z-score standardization involves transforming information from various measurement ranges into a single common scale through Z-score calculations, which enables data point comparison [30,31]. The specific formula is as follows:

$$Z\text{-}score = \frac{value - mean}{Standard\ Deviation} \tag{2}$$

Calculation of the Covariance Matrix for Standardized Samples

Based on the standardized data, calculate its covariance. The calculation formula is as follows:

$$r_{ij} = \frac{1}{n-1} \sum_{k=1}^{n} Z_{ki} Z_{kj} \tag{3}$$

In this formula, the element r_{ij} is the covariance between the i-th variable and the j-th variable. Use the obtained covariance r_{ij} to construct the covariance matrix R for the standardized samples.

Calculation of Eigenvalues and Eigenvectors

After completing the data standardization and constructing the covariance matrix R, the next step is to solve for the eigenvalues and eigenvectors of the covariance matrix. The characteristic equation of matrix R needs to be solved to achieve this result. The resulting eigenvalues are $\lambda 1$, $\lambda 2$, $\lambda 3$, … λp, with each eigenvalue corresponding to an eigenvector. These eigenvectors indicate the directions of the principal components. For example, the p-th eigenvector can be expressed as $a_1 = [a_{11}, a_{21}, \ldots a_{p1}]$, and so on.

Calculation of Contribution Rate and Cumulative Contribution Rate

To evaluate the importance of each principal component, it is necessary to calculate its contribution rate and cumulative contribution rate. For the i-th principal component, its contribution rate P_i is defined as the ratio of its eigenvalue to the sum of all eigenvalues. This indicator helps us determine how many principal components to retain. The formula is as follows:

$$p_i = \frac{\lambda_i}{\sum_{k=1}^{p} \lambda_k} \quad (4)$$

Determination of the Number of Principal Components

In practical applications, it is not necessary to retain all principal components. In this paper, we select those principal components with eigenvalues greater than 1 because they make significant contributions to the variation in the original data [32].

Comprehensive Evaluation and Weighted Sum

The final step involves a comprehensive evaluation of the selected principal components. The linear weighted value for the *m*-th principal component is calculated as follows:

$$F_m = a_{m1}Z_1 + a_{m2}Z_2 + \dots + a_{mk}Z_k \quad (5)$$

Where Z_i represents the standardized variable. Then, by summing the weighted values of these *k* principal components, we obtain the final comprehensive evaluation score *F*.

3.3.2. Comparative Analysis Method

Calculation of the Average Score of the Overall Company

The core focus of this paper is industry-level performance, which evaluates the overall development status of Chinese listed fishery companies through comparative analysis. The first step is to calculate the principal component comprehensive competitiveness score of all sample companies each year.

The first step is to calculate principal component composite competitiveness scores for all sample companies in each year. Based on these scores, we calculate the annual average scores for fishery companies, non-fishery companies, and all agricultural listed companies (including fishery companies) separately. Through these calculations, we can clearly observe the performance of fishery companies, non-fishery companies, and agricultural companies in different years. To demonstrate the trend of the company's competitiveness, we standardized the calculated annual average score using the following formula:

$$AG_{total} = \frac{S_1 + S_2 + \dots + S_{44}}{46} \times 100 \quad (6)$$

$$AG_{fishery} = \frac{V_1 + V_2 + \dots + V_8}{8} \times 100 \quad (7)$$

$$AG_{non-fishery} = \frac{W_1 + W_2 + \dots + W_{38}}{38} \times 100 \quad (8)$$

Where AG_{total} represents the overall annual average score for all agricultural listed companies, $AG_{fishery}$ indicates the annual average score for listed fishery companies. $AG_{non\text{-}fishery}$ represents the annual average score of non-fishery listed companies.

Visualization Analysis

This paper employs Origin 2024 for visualization analysis to illustrate the changes in the competitiveness of listed fishery companies and their relative differences compared to the overall level of agriculture-related listed companies. We will visualize the calculated annual average scores, analyze the performance of listed fishery companies relative to the overall benchmark, and thoroughly examine the evolution of their various competitiveness indicators.

4. Results

4.1. KMO Test and Bartlett's Test

The results of the KMO and Bartlett sphericity tests are shown in **Table 2**. The KMO value is 0.632. According to the standards for the KMO test, a value greater than 0.5 indicates strong correlations between variables, making it suitable for factor analysis. A KMO value greater than 0.6 suggests that the data has a good factor structure, appropriate for principal component analysis [33]. The KMO value of 0.632 indicates that the data has a favorable factor structure, suitable for principal component analysis.

Bartlett's sphericity test is used to check whether the correlation matrix between variables is an identity matrix. If the *p*-value is less than 0.05, the null hypothesis is rejected, indicating significant correlations between variables, which makes factor analysis appropriate [34]. The *p*-value from Bartlett sphericity test is far less than 0.05, indicating significant correlations between variables, further supporting the rationality of conducting principal component analysis.

Table 2. Test table of KMO and Bartlett.

KMO	Bartlett Sphericity Test		
	Approximate Chi Square	**df**	**Sig.**
0.632	4657.164	78	0.000

4.2. Principal Component Extraction

By analyzing the information content of the extracted principal components, we identified five principal components with eigenvalues greater than 1. Their variance explained rates are 26.03%, 17.143%, 15.371%, 11.895%, and 8.727%, respectively, with a cumulative variance explained rate of 79.165%. These components effectively represent the 13 original indicators [32]. The results of the variance explained rates are shown in **Table 3**.

The rotated component matrix is shown in **Table 4**. We define and name the five extracted principal components as follows:

The first principal component, F1, has a high load on indicators such as return on equity, return on total assets, sales net profit margin, and operating profit margin, all of which directly reflect the ability of companies to obtain profits through business activities. Therefore, F1 is defined as the "Profitability Factor."

The second principal component, F2, has prominent loadings on inventory turnover rate, current asset turnover rate, and total asset turnover rate. This highlights the company's management and operational capacity of assets; thus, it is named the "Operational Capacity Factor."

The third principal component, F3, has loadings close to 1 on debt-to-asset ratio and equity multiplier. These two indicators primarily measure the capital structure and financial leverage utilization of the company; hence, F3 is defined as the "Capital Structure Factor."

The fourth principal component, F4, has the highest loadings on the total asset growth rate and monetary fund growth rate. This reflects the trend of corporate scale expansion and capital accumulation; therefore, it is named the "Growth Factor."

The fifth principal component, F5, has significant loadings on the current ratio and the quick ratio. These two indicators are core measures of a company's short-term debt repayment capability; thus, F5 is defined as the "Debt Repayment Capability Factor."

The five principal components correspond to different dimensions of company competitiveness, providing a foundation for subsequent comprehensive evaluation.

Table 3. Eigenvalues and contribution rate of main factors.

Factors	Initial Eigenvalue			Rotation Sums of Squared Loadings		
	Eigenvalues	**Contribution Rate (%)**	**Cumulative Contribution Rate (%)**	**Eigenvalues**	**Contribution Rate (%)**	**Cumulative Contribution Rate (%)**
1	3.384	26.030	26.030	3.087	23.744	23.744
2	2.229	17.143	43.173	2.382	18.321	42.066
3	1.998	15.371	58.543	2.010	15.461	57.526
4	1.546	11.895	70.439	1.670	12.844	70.370
5	1.134	8.727	79.165	1.143	8.795	79.165
6	0.871	6.697	85.863			
7	0.709	5.452	91.315			
8	0.369	2.835	94.150			
9	0.330	2.540	96.691			
10	0.229	1.758	98.449			
11	0.196	1.504	99.953			
12	0.005	0.041	99.994			
13	0.001	0.006	100.000			

Table 4. The factor load table after rotation.

Index	Principal Factor				
	F1	**F2**	**F3**	**F4**	**F5**
X1	0.756				
X2	0.870				
X3	0.928				
X4	0.923				
X5		0.857			

Table 4. *Cont.*

Index	Principal Factor				
	F1	**F2**	**F3**	**F4**	**F5**
X6		0.907			
X7		0.875			
X8			0.998		
X9			0.998		
X10				0.912	
X11				0.903	
X12					0.758
X13					0.738

4.3. Score Calculation

Based on the factor score coefficient matrix obtained from principal component analysis (**Table 5**), we can calculate the score functions for each of the five principal components for every listed agriculture-related company annually. The formulas are as follows:

$$\begin{gathered} F_1 = 0.250X_1 + 0.278X_2 + 0.31X_3 + 0.309X_4 - \\ 0.053X_5 - 0.011X_6 - 0.017X_7 + 0.004X_8 + \\ 0.005X_9 - 0.01X_{10} - 0.031X_{11} + \\ 0.005X_{12} - 0.036X_{13} \end{gathered} \tag{9}$$

$$\begin{gathered} F_2 = -0.016X_1 + 0.023X_2 - 0.049X_3 - \\ 0.055X_4 + 0.372X_5 + 0.388X_6 + 0.376X_7 \\ - 0.009X_8 - 0.009X_9 - 0.062X_{10} - \\ 0.008X_{11} - 0.005X_{12} + 0.011X_{13} \end{gathered} \tag{10}$$

$$\begin{gathered} F_3 = 0.0002X_1 - 0.01X_2 + 0.014X_3 + 0.011X_4 \\ + 0.032X_5 - 0.022X_6 - 0.037X_7 + 0.497X_8 + \\ 0.497X_9 + 0.016X_{10} + 0.0004X_{11} - \\ 0.033X_{12} + 0.018X_{13} \end{gathered} \tag{11}$$

$$\begin{gathered} F_4 = -0.023X_1 + 0.015X_2 - 0.025X_3 - \\ 0.024X_4 - 0.03X_5 - 0.032X_6 - 0.029X_7 + \\ 0.008X_8 + 0.007X_9 + 0.559X_{10} + \\ 0.547X_{11} - 0.02X_{12} + 0.025X_{13} \end{gathered} \tag{12}$$

$$\begin{gathered} F_5 = -0.018X_1 - 0.02X_2 - 0.004X_3 - 0.002X_4 \\ - 0.069X_5 - 0.023X_6 + 0.102X_7 - 0.005X_8 - \\ 0.002X_9 - 0.021X_{10} + 0.026X_{11} + \\ 0.663X_{12} + 0.649X_{13} \end{gathered} \tag{13}$$

Using the contribution rates corresponding to each principal component as weights, we perform a weighted sum for each principal component. This results in a function used to calculate the annual competitiveness of each listed agriculture-related company. The formula is as follows:

$$F = \frac{23.744F_1 + 18.321F_2 + 15.461F_3 + 12.844F_4 + 8.795F_5}{79.165} \tag{14}$$

Table 5. Factor score coefficient matrix.

Index	Principal Factor				
	F1	**F2**	**F3**	**F4**	**F5**
X1	0.250	−0.016	0.000	−0.023	−0.018
X2	0.278	0.023	−0.010	0.015	−0.020
X3	0.310	−0.049	0.014	−0.025	−0.004
X4	0.309	−0.055	0.011	−0.024	−0.002
X5	−0.053	0.372	0.032	−0.030	−0.069
X6	−0.011	0.388	−0.022	−0.032	−0.023
X7	−0.017	0.376	−0.037	−0.029	0.102
X8	0.004	−0.009	0.497	0.008	−0.005
X9	0.005	−0.009	0.497	0.007	−0.002
X10	−0.010	−0.062	0.016	0.559	−0.021
X11	−0.031	−0.008	0.000	0.547	0.026
X12	0.005	−0.005	−0.033	−0.020	0.663
X13	−0.036	0.011	0.018	0.025	0.649

4.4. Analysis of Company Competitiveness

We calculated the average competitiveness scores for all listed agriculture-related companies and listed fishery companies each year, and standardized the annual averages to more comprehensively analyze the trends in competitiveness changes. The specific data is shown in **Table 6**.

Table 6. Average comprehensive scores from 2018 to 2024.

	2018	2019	2020	2021	2022	2023	2024
Total	2.325	1.860	8.602	2.237	−5.773	−5.981	−3.270
Fishery	−1.931	−24.278	2.960	−9.865	0.766	3.497	−21.119
Non-Fishery	3.221	7.363	9.790	4.785	−7.150	−7.065	0.488

To visually illustrate the trend of these data changes, we created a visualization and an annual average comprehensive score trend chart, as shown in **Figure 1**. This chart depicts the comparative trajectory of fishery listed companies and non-fishery listed companies from 2018 to 2024. The graph shows that compared to non-fishery companies, the competitiveness scores of listed fishery companies fluctuate more significantly, providing empirical support for Hypothesis 2.

The scores of listed agriculture-related companies experienced an increase from 2018 to 2020, driven by policy incentives and industrial upgrading. In 2018, the Central Document No. 1 first introduced the "Rural Revitalization Strategy," focusing on agricultural supply-side structural reforms. This initiative aimed to optimize grain varieties, promote large-scale operations, and apply agricultural technology. Companies improved efficiency through the introduction of smart farming machinery and the development of green planting practices[35]. However, in 2021 and 2022, the scores of these companies plummeted, likely due to external shocks and cost pressures. The pandemic disrupted the flow of agricultural supplies and delayed farming activities. The rebound in 2023 and 2024 can be attributed to policy support and post-pandemic market recovery. In 2023, the Central Document No. 1 proposed "Accelerating the Construction of an Agricultural Powerhouse," emphasizing the expansion of high-standard farmland and agricultural insurance coverage. Companies leveraged digital transformation to optimize their supply chains, leading to a temporary resurgence in competitiveness[36].

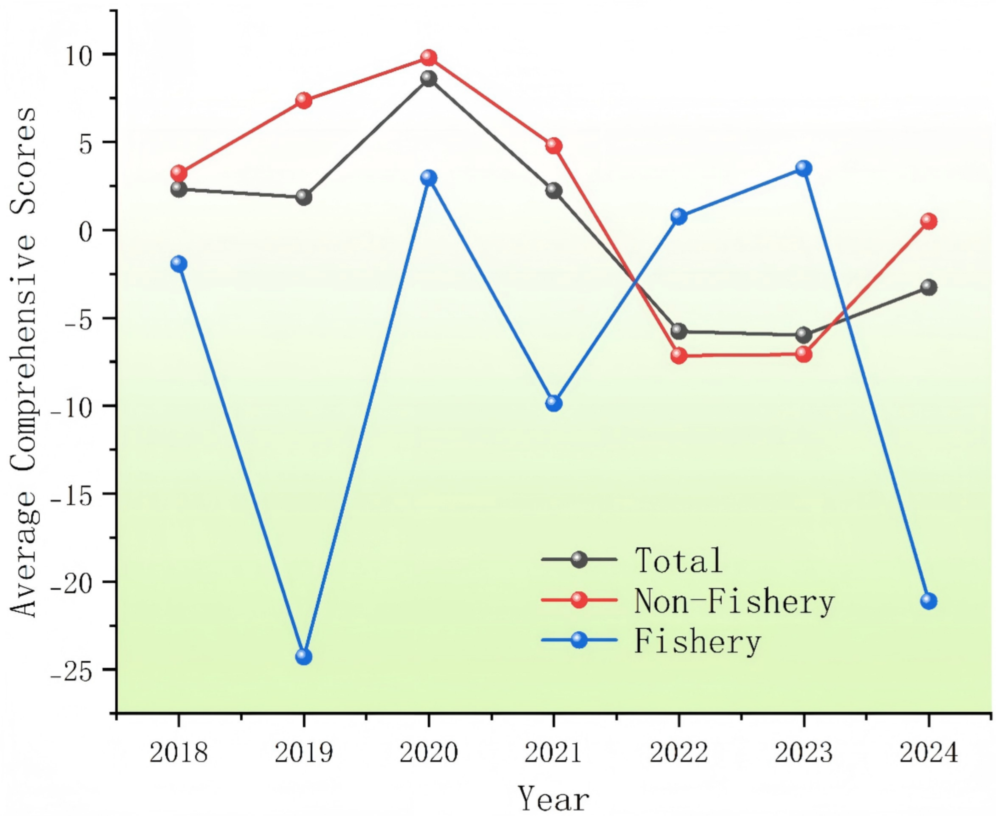

Figure 1. Average comprehensive score trend from 2018 to 2024.

The volatility of listed fishery companies shows strong connections to their industry-specific characteristics. The scores decreased from −1.931 to −24.278 during 2018 and 2019 because of changes in the external environment and market pressure. The rising US-China trade conflict caused seafood export orders to drop dramatically, which reduced corporate revenue levels [37]. The second significant decline in 2021 reflects the fragility of the fishery industry's ability to resist risks. The repeated outbreaks of the COVID-19 pandemic in China in 2021 have led to a downturn in the catering industry, putting pressure on fishery companies. The recovery from 2022 to 2023 was driven by consumption revival and policy support. In 2022, the acceleration of "Marine Powerhouse" construction saw the state promoting innovation in aquaculture seed industries. Companies expanded into retail markets through new formats like ready-to-cook meals, leading to a temporary rebound in competitiveness [38]. The sharp decline in 2024, triggered by the nuclear wastewater discharge incident, was merely the catalyst for deeper systemic risks within the industry. The public lost faith in seafood safety while marine environmental shifts caused fishery resources to become unstable, and economic downturns cut down on seafood market demand. The characteristic of fishery companies relying heavily on market conditions was further exacerbated. This persistent instability, combined with consistently lower average performance over the sample period, confirms Hypothesis 2: Chinese listed fishery companies display significantly higher competitiveness volatility and lower overall levels than their agricultural counterparts.

The F1–F5 factors extracted by principal component analysis can well reflect the core dimensions of the competitiveness of Chinese listed fishery companies, providing a quantitative basis for understanding the key constraints on industry development, as shown in **Figure 2** and **Table 7**. Profitability Factor (F1), as the foundation for the survival and development of companies, its score fluctuation can best reflect the impact of the market environment. The F1 score of fishery companies was negative from 2019 to 2024, and remained in the negative range for a long time, with a large annual fluctuation range, far higher than the fluctuation range of non-fishery companies. This trend indicates that when facing internal and external pressures such as rising costs and fluctuations in orders, the compression speed and depth of profit margins of fishery companies exceed the average level of the agricultural industry.

Figure 2. Radar chart of principal components of companies from 2018 to 2024.

Table 7. Average scores of each principal component of the listed fishery companies from 2018 to 2024.

Year	F1		F2		F3		F4		F5	
	Non-Fishery	Fishery	Non-Fishery	Fishery	Non-Fishery	Fishery	Non-Fishery	Fishery	Non-Fishery	Fishery
2018	22.954	15.337	−14.997	−10.608	−9.106	−10.021	−11.698	−22.145	31.351	13.265
2019	27.970	−55.245	6.819	−7.014	−13.493	−1.035	1.250	−21.157	−1.547	−22.054
2020	33.442	−4.190	−1.776	−15.263	−8.381	11.329	8.954	−17.006	3.195	74.672
2021	−29.761	−16.232	−16.304	−0.634	40.993	6.411	58.922	−25.022	−0.728	−18.380
2022	−6.089	−3.396	−6.570	−10.635	−4.571	−2.721	−9.106	9.761	−12.900	28.740
2023	−26.876	−15.990	21.178	−21.573	−8.384	49.756	−2.179	−12.128	−17.228	10.831
2024	2.473	−34.825	29.633	−19.688	−8.483	0.556	−21.050	−31.506	−18.362	−10.034

In terms of Capital Structure Factor (F3), the performance of fishery companies exhibits cyclical fluctuations. In 2018, the F3 score was −10.021, and in 2022 it was also negative −2.721, but neither of these low points exceeded the lowest value of −13.493 for non-fishery companies. In addition, the F3 score of the fishery companies increased to 11.329 in 2020, but this short-term improvement did not translate into long-term capital structure optimization ability. After 2021, the F3 score fell again, indicating that fishery companies still have shortcomings in debt management and diversified financing channels.

In terms of Growth Factor (F4), the performance of fishery companies is particularly noteworthy. The F4 score of fishery companies has been at a low level for seven years, briefly turning to 9.761 in 2022, and then continuing to decline to −31.506 between 2023 and 2024, far below the F4 level of non-fishery companies. This performance confirms hypothesis H1, that fishery companies lack sustainable growth drivers. In contrast, non-fishery companies have relatively higher F4 scores and exhibit stronger endogenous growth elasticity.

In terms of Operational Capacity Factor (F2) and Debt Repayment Capability Factor (F5), the performance of fishery companies shows significant fluctuations. From the perspective of Operational Capacity Factor (F2), its annual score has undergone significant changes, deteriorating from −10.608 in 2018 to −15.263 in 2020 and dropping to −21.573 in 2023. Although the fluctuation range of F2 in non-fishery companies is also relatively large, the length and depth of its negative range are significantly smaller than those in fishery companies, indicating that fishery companies face more severe challenges in asset turnover, cost control, and other operational aspects. In terms of the Debt Repayment Capability Factor (F5), its annual score fluctuates greatly. In 2020, the F5 score of fishery companies reached a peak of 74.672, far exceeding their historical average and the score of non-fishery companies during the same period (3.195). In 2024, F5 sharply declined to −10.034, a decrease of 84.706, far exceeding the decline rate of non-fishery companies during the same period. The abnormally high value of F5 in 2020 may be related to policy subsidies that year, while the decline in 2024 coincides with the timing of Japan's nuclear wastewater discharge event [39]. Although this temporal correlation provides observational clues, current data can only indicate the potential correlation between its fluctuations and external events, and cannot yet verify whether its vulnerability has systematic characteristics.

5. Discussion

This paper uses principal component analysis (PCA) to construct a comprehensive evaluation framework that includes five dimensions: profitability capability, operational capability, capital structure, growth capability, and debt repayment capability. It evaluated the competitiveness of Chinese listed fishery companies from 2018 to 2024. The main research findings are as follows: Firstly, the PCA method effectively deconstructs and quantifies the complex internal structure of the competitiveness of fishery listed companies, demonstrating strong explanatory power. Secondly, the volatility of the competitiveness of listed fishery companies greatly exceeds the overall level of non-fishery listed companies and listed agricultural companies. Thirdly, the impact paths of different types of external shocks on various dimensions of competitiveness exhibit heterogeneity. Fourthly, throughout the entire observation period, the growth capacity of listed fisheries companies remained weak, indicating long-term systemic bottlenecks in scale expansion and technological iteration.

This paper has several limitations that can guide future research. Firstly, the sample is limited to listed companies with publicly available financial data and does not include a large number of potentially more vulnerable small and medium-sized non-listed fishery companies. This limitation limits the generalizability of research conclusions, as non-listed companies often operate under different resource constraints, governance structures, and market access conditions. Future research can utilize other data sources to include non-listed companies.

Secondly, although the constructed indicator system covers a large number of financial dimensions, it does not include key non-financial indicators such as brand value, consumer confidence, ESG performance, and marine ecosystem health indicators [40–43]. These omissions may lead to the inability to fully capture the long-term sustainability of the competitiveness of the fisheries sector. For example, consumer confidence in seafood safety can affect market demand, but these indicators were not quantified in this paper. Future research can use more dimensions of competitiveness indicators to expand the understanding of this concept.

Thirdly, the current analysis lacks sufficient perspectives to distinguish the sub-sectors of fisheries, such as aquaculture and offshore fishery companies. The business strategies of different fisheries sub-industries have certain differences [43,44]. Aquaculture companies may prioritize capital-intensive infrastructure investments and face climate-related production fluctuations, while offshore fishery companies are more susceptible to the impact of international trade regulations and seasonality. Due to the limited sample size, this paper categorizes all listed fisheries companies into one group, masking potential structural differences in their operational risks and competitive strategies. Future research using larger datasets can conduct comparative analysis of sub-sectors, providing targeted policy recommendations for different business models within the industry.

Finally, the causal explanation for changes in competitiveness in this paper is qualitative, focusing on observed patterns rather than establishing strict quantitative relationships. Although longitudinal analysis identifies the correlation between possible external shocks and competitiveness, it does not quantify the degree or direction of these interactions. Future research can use advanced econometric techniques such as Granger causality tests, vector autoregression (VAR) models, or machine learning based feature importance analysis to clarify the complex interactions between environmental, economic, and policy variables [45].

6. Conclusions and Recommendations

This paper employs Principal Component Analysis (PCA) to construct a multi-dimensional evaluation system, systematically assessing the competitiveness of listed Chinese fishery companies from 2018 to 2024. The empirical results indicate that the competitiveness of fishery companies exhibits high volatility and high fragility, with their evolution influenced by external policies and environmental shocks. While industry support policies can temporarily optimize capital structure and profitability, negative external shocks such as the COVID-19 pandemic and nuclear wastewater discharge have an immediate and substantial impact on their competitiveness. Additionally, the paper highlights long-term systemic bottlenecks in the growth capability dimension of listed fishery companies. The main contribution lies in linking macro-level policy changes, environmental damage, and micro-level financial performance, providing a data-driven framework to diagnose the systemic vulnerability of the fisheries sector.

Based on the "high volatility and high vulnerability" characteristics and sensitivity to external shocks of fishery listed companies revealed by research, a tiered policy tool system should be established to systematically enhance industry resilience from three dimensions: short-term risk hedging, long-term growth empowerment, and cross-departmental collaboration, as illustrated in **Figure 3**. In the short term, efforts should focus on risk mitigation and cash flow stabilization by implementing an emergency subsidy mechanism and hedging market fluctuations through low-interest loans and climate risk insurance. Concurrently, pilot programs for

AI-driven aquaculture technologies should be promoted to enhance corporate operational efficiency through automated disease monitoring and precision feeding systems.

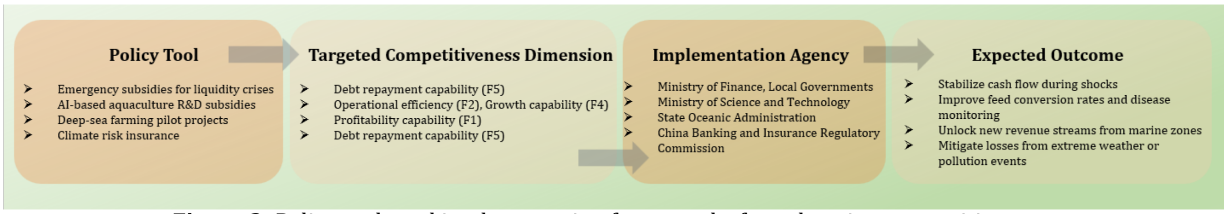

Figure 3. Policy tools and implementation frameworks for enhancing competitiveness.

For the long term, it is imperative to reinforce structural reforms by establishing a dedicated fund for deep-sea aquaculture, offering supporting sea use rights and tax incentives to stimulate growth potential. Additionally, a cross-departmental coordination mechanism should be set up, involving the Ministry of Finance, the Ministry of Science and Technology, the State Oceanic Administration, and financial regulatory bodies, to dynamically adjust the policy toolkit, such as optimizing insurance coverage every quarter in response to global environmental risks. These measures can help offset the impact of short-term external shocks, overcome growth bottlenecks through technological empowerment and industrial chain integration, and provide support for enhancing the resilience of fisheries under the "Maritime Power" strategy.

Author Contributions

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Conflicts of Interest

The authors declare no conflict of interest. During the writing process of this work, the authors used the Qwen large language model in order to improve language only. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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