Original Research Articles

Multiple paths to optimize input-output efficiency of Chinese fishery listed companies: A composite study of Tobit and fsQCA

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Against the background of global concern for aquatic product quality and safety, and for the sustainable development of fisheries, the operations and management of listed fishery companies are facing significant challenges, and the multidimensional optimization of input-output efficiency has become a key issue. This paper uses data envelopment analysis (DEA) and the Tobit regression model to assess the input-output efficiency and its influencing factors of A-share fishery listed companies from 2019 to 2023, and identifies multiple paths to high input-output efficiency using the fuzzy set qualitative comparative analysis (fsQCA) method. The results show that: (1)enterprise scale efficiency and comprehensive technical efficiency have not reached the production frontier and still have potential for improvement; (2)ESG performance and ownership concentration show a positive relationship with enterprise input-output efficiency, while return on equity, asset liability ratio and enterprise scale show a negative effect; (3)individual antecedents are not sufficient to constitute the necessary conditions for enterprises to improve input-output efficiency, and there are four combinations of paths to improve efficiency. The above conclusions are of practical significance for fishery enterprises to avoid risks and promote healthy, safe, and sustainable development.

1. INTRODUCTION

The quality and safety of aquatic products, and their sustainable development, have become a key issue of global concern. Fishery resources not only support the nutritional security of human beings but also are indispensable for guaranteeing global food security and promoting economic growth (FAO, 2018).[1] However, amid global climate change, the gradual depletion of fishery resources, and the growing problem of environmental pollution, fishery enterprises are facing increasingly severe challenges, especially in operational and resource utilization efficiency. The input-output efficiency of listed fishery companies is a key indicator of the industry's sustainability and competitiveness. Input-Output Efficiency refers to the number of effective products or services an enterprise can produce with fixed resource inputs, and it is a key indicator of an enterprise's operational efficiency and the rationality of resource allocation. Its optimization not only significantly drives the economic performance of enterprises but also contributes to the coupling process of the sustainable development of the marine economic system. Exploring the effective output levels of fishery enterprises and balancing resource utilization and ecological protection have become core issues for all countries. Therefore, exploring the multidimensional optimization path for input-output efficiency of listed fishery companies has important theoretical value and provides practical references for policymakers and enterprise managers.

The input-output efficiency of enterprises and its influencing factors have long been a central topic in both academic research and policy practice. However, systematic studies focusing on specific industries—particularly listed fishery companies—remain notably insufficient. Throughout the research dynamics at home and abroad, there are few direct studies on the input-output efficiency of fishery listed companies, but the research on the input-output efficiency of the company and the financial performance of

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the enterprise has been the focus of the academic community. According to the existing literature, scholars have conducted numerous studies on enterprise input-output efficiency, and most of these studies use the DEA method. Charnes was the first to propose the use of the DEA method to measure the input-output efficiency in 1978 (Charnes et al., 1978).[2] By 1984, Banker proposed a framework for decomposing scale and technical efficiencies based on the DEA model (Banker et al., 1984),[3] which provided a theoretical basis for identifying the sources of firm inefficiency. This approach has become a common tool for efficiency assessment by virtue of its nonparametric nature and its ability to handle multiple input-output relationships. Dong et al. used SWOT analysis to comprehensively analyze the external and internal environments affecting the efficiency of China's sports industry, and applied data envelopment analysis to evaluate SWOT efficiency and introduced the PEST model, focusing on the empirical analysis of SWOT efficiency of regions and provinces using its extended BCC model (Dong et al., 2021).[4] Besides, Wen H et al. used the fixed-effects stochastic frontier approach (TFE-SFA) to measure the input-output efficiency of the ICT equipment manufacturing and ICT service industries and to examine regional differences and dynamic evolution (Hu et al., 2023).[5] Existing research has established the methodological foundation of Data Envelopment Analysis (DEA) for efficiency evaluation, gradually shifting from overall efficiency measurement to the decomposition of technical and scale efficiencies, thereby providing crucial analytical tools for subsequent studies.

As research deepens, more scholars are exploring the factors affecting the industry's input-output efficiency. To further explore the factors affecting efficiency, the Tobit model has been widely used to analyze data with truncated distributions (Tobin, 1958),[6] especially in analyzing the impact of corporate governance characteristics or financial indicators on efficiency. Shao and Wang measured the input-output efficiency of China's software service industry using the SFA model and analyzed the main factors affecting it using the Tobit model (Shao and Wang, 2013).[7] Wei and Yan used data envelopment analysis to examine regional differences in the input-output efficiency of agroecological environmental protection in China's regions in 2018, and used the Tobit model to examine the factors influencing agroecological environmental protection efficiency (Wei and Yan, 2021).[8] Yang et al. used the super-efficiency slacks-based measure (SBM) model to measure the financing efficiency of biomedical listed companies in China, applied the Malmquist index method to reflect the changes in the financing efficiency of biomedical listed companies, and con0 constructed a model of the influencing factors of the financing efficiency through the Tobit model (Yang et al., 2024).[9] Wu and others combine the SBM, Malmquist, and Tobit models to form a comprehensive assessment framework to assess current efficiency and analyze the trend of efficiency changes and influencing factors, which provides a new methodology to learn from for the efficiency assessment of government open data platforms (Wu et al., 2024).[10]

It is evident that the Tobit model has become a standard method for analyzing the determinants of efficiency when dealing with limited-dependent variables. Nevertheless, it fundamentally relies on assumptions of linearity and independence, making it difficult to capture synergistic and configurational effects among multiple factors. Most of the existing literature still adopts the traditional efficiency assessment method and pays less attention to the multi-path combination of enterprise efficiency improvement. Existing studies mainly focus on the influence of single factors, such as enterprise size, financial structure, and shareholder characteristics, on efficiency, and the systematic analysis of multi-factor interactions and path combinations remains insufficient.

In recent years fsQCA method has been gradually introduced into efficiency research, revealing the diversity and complexity of corporate efficiency improvement from the perspective of path combination (Ragin, 2009).[11] Shi et al. used fsQCA to analyze the antecedent patterns and driving paths of green technology innovation efficiency in tourism from a digital economy perspective (Shi et al., 2024).[12] Wei et al. constructed a dynamic network DEA model based on global weights and combined it with fsQCA to explore the paths that drive the innovation efficiency of China's high-tech industries (Wei et al., 2024).[13] Wang and others used the DEA-BCC model to measure the efficiency of China's sports industry in recent years and used the efficiency value in 2021 as the outcome variable to analyze multiple paths to improve its efficiency using fsQCA (Wang et al., 2024).[14] Although these methods have been widely used in industries such as agriculture and manufacturing, there are few relevant studies for the listed fishery companies, and the current status of their efficiency and the mechanisms that affect it have not yet been fully explored. While these studies demonstrate the advantages of fsQCA in revealing multiple pathways for efficiency improvement, existing findings have predominantly concentrated on industries such as high technology and sports. Research in the fishery sector—an industry characterized by both resource dependence and policy sensitivity—remains relatively scarce.

In addition, the role of environmental, social, and governance (ESG) factors in corporate efficiency is usually overlooked, even though ESG has been widely recognized as a key factor affecting long-term corporate performance (Friede et al., 2015).[15] Zhou and Cao found that good ESG performance can significantly improve the financing efficiency of manufacturing firms (Zhou and Cao, 2024).[16] Fang's findings provide empirical evidence that firms promote operational efficiency through ESG investment (Fang and Liu, 2024).[17] Qi suggests that good ESG performance can improve the efficiency of corporate working capital management by enhancing supply chain voice and alleviating financing constraints (Qi and Wu, 2024).[18] Although the positive correlation between ESG (Environmental, Social, and Governance) factors and corporate efficiency has been increasingly validated, the specific mechanisms by which ESG dimensions affect resource allocation and operational efficiency in fishery enterprises—particularly their roles within multifactor configurations—still require in-depth exploration.

Therefore, the current existing research still has the following shortcomings:(1) the established literature has studied corporate input-output efficiency and its influencing factors from different perspectives, but little research has been conducted on fishery listed companies.(2) Research has been conducted in different fields using DEA, the Tobit model, and fsQCA, but the three have not been combined for the theoretical and synergistic development of empirical analyses in the field of fisheries. (3) The key role of ESG in promoting the sustainable development of listed companies in the fishery industry, as well as companies in other fields, has not been adequately reflected in the existing literature.(4) Most of the current studies rely on empirical data from developed countries, while there is a relative lack of empirical studies on fishery companies in developing countries, especially in China, which, to a certain extent, restricts the universality of the conclusions of the studies and their value as a policy guide.

The above research gaps limit in-depth understanding of the efficiency-enhancement mechanism in fishery enterprises and hinder the formulation of targeted policies and management recommendations. To summarize, there is still room for further expansion of existing research in terms of theoretical depth and breadth of application. To fill this research gap, this paper takes the financial data of Chinese A-share fishery listed companies from 2019-2023 as the research sample, and aims to comprehensively assess the input-output efficiency of Chinese fishery listed companies and explore four optimization paths from a multi-dimensional perspective through the organic combination of DEA, Tobit, and fsQCA methodologies, so as to fill the gaps in the existing research. Based on empirical analysis, we emphasize the important role of ESG in improving input-output efficiency and the sustainable development of listed fishery companies. As a resource-dependent industry, fisheries face dual pressures of resource depletion and environmental regulation, making their efficiency optimization a paradigmatic case for transforming the marine economy.

The marginal contributions of this paper are: first, this paper systematically assesses for the first time the efficiency changes of Chinese A-share fishery listed companies in the last five years, which enriches the empirical basis of efficiency research; second, it systematically assesses the current efficiency status of Chinese fishery listed companies and their influencing factors; third, it reveals four typical path combinations of corporate efficiency improvement, namely, "ESG-Driven", "ESG-Scale Driven", "ESG-Return on equity-Shareholder ownership Driven" and "Small scale-Shareholding Diversified". By deeply analyzing the mechanisms and improvement paths of fishery enterprise efficiency, this paper not only enriches the theoretical content of efficiency research but also provides practical solutions for fishery enterprises to achieve green and sustainable development.

At the theoretical level, previous studies have mostly focused on traditional financial factors. This research is among the first to integrate "ESG performance"—a non-financial indicator—with the input-output efficiency of fishery enterprises, thereby expanding the boundary of factors influencing efficiency. At the methodological level, targeting the fishery sector as a special industry, this study innovatively combines the "net effect" analysis of the DEA-Tobit model with the "configuration effect" analysis of fsQCA. This approach not only identifies the impact of individual factors but also reveals the complex pathways leading to high efficiency under the concurrent action of multiple factors, providing a new perspective for understanding the driving mechanism of enterprise efficiency.

The remaining structure of this paper is organized as follows: the second part introduces the research design and methodology, describing the data sources, research variables, and models adopted; the third section analyses the empirical results; and the fourth section develops the discussion.

2. MATERIALS AND METHODS

2.1. DATA SOURCES

This paper analyzes seven A-share fishery listed companies in China and selects financial statement data from 2019-2023 as the research sample to form a panel dataset. Data are obtained from the Wind database, and companies with missing important financial data are excluded. The ESG data is sourced from third-party ratings in the Wind Database, with the overall score derived from the average of the three dimensions: environmental, social, and governance. The ESG assessment framework in the Wind Database covers three major dimensions, 29 thematic issues, and over 2,000 data points to evaluate a company's ESG performance. A higher ESG score indicates better ESG performance by the listed company.

2.2. DEFINITIONS AND DESCRIPTIONS OF VARIABLES

Drawing on existing studies and considering the operating characteristics of fishery-listed companies, this paper identifies the following input-output indicators and explanatory variables (Table 1).

Financial cost reflects the strength of an enterprise's capital investment. In the production and operation process, enterprises usually rely on their own capital and external financing (such as bank loans and bonds) to maintain operations, and the level of financial expenses directly determines the enterprise's cost of capital acquisition, which, in turn, affects overall input costs. R&D costs reflect the investment of fishery enterprises in aquatic product breeding and biotechnology development. R&D activities can not only increase output quantity but also optimize product quality and increase product value. Compared with traditional input factors such as capital and labor, R&D better reflects enterprises' investment in improving resource allocation efficiency. The shareholding ratio of major shareholders is a significant variable for measuring the control and influence of shareholders over the enterprise. A large shareholder with a high shareholding ratio not only

Table 1. Variable names and meanings

Form	Variable name	Meaning
Input indicators	Financial cost	Related expenses incurred in raising funds in the production and operation of enterprises
	R&D cost	All expenditures invested by enterprises in research and development activities
	Shareholding ratio of major shareholders	Shares held by major shareholders holding a large number of shares in the company
	Top three executive compensation	The sum of the top three executives' salaries
Output indicators	Return on total assets	(EBIT/total assets) x 100%
	Growth rate of revenue	(Operating income for the current period−Operating income for the previous period)/Operating income for the previous period x 100%
Explanatory variable/ Conditional variable	ESG performance	Combining the environmental, social and governance performance of an enterprise into an overall score through weight allocation
	Return on equity	(Net profit/average Net assets) x 100%
	Asset liability ratio	(Total liabilities/Total assets) x 100%
	Enterprise scale	Measured by taking the logarithm of the total number of enterprises
	Ownership concentration	Measured by the shareholding ratio of the top five shareholders

provides financing facilities for the enterprise and reduces the cost of capital (reduces finance costs), but also tends to focus on the enterprise's long-term development to optimize long-term output efficiency. The shareholding ratios of major shareholders can be regarded as an input variable in the allocation of corporate control, and a reasonable shareholding structure can help stabilize corporate governance and promote sound business operations. In addition, executive compensation, as an incentive mechanism for the core management team of an enterprise, reflects the strength of an enterprise's investment in top management talent. The level of compensation usually matches the decision-making ability, resource integration ability and strategic planning ability of executives, and high pay often means that firms expect to leverage the leadership of managers to improve operational performance. Executive compensation can be regarded as one of the key input elements of corporate governance efficiency. Therefore, this study takes financial cost, R&D cost, shareholding ratio of major shareholders and top three executive compensation by amount as input indicators to measure the efficiency of fishery enterprises. Total return on assets is a financial indicator that measures an enterprise's ability to utilize all assets to generate profits and reflects the efficiency of its management in resource allocation. In this study, total return on assets reflects the operational efficiency of listed fishery companies.

Return on total assets is a financial indicator of the profitability of an enterprise's overall assets, directly reflecting the enterprise's ability to convert factors of production such as capital, labor, and management into revenue. A higher return on total assets means that, for the same asset size, the enterprise can generate more profits, indicating better input-output efficiency. The growth rate of revenue measures the increase in an enterprise's revenue over a specific time period, reflecting its business expansion capacity and market competitiveness. This indicator directly reflects the enterprise's profitability and business performance. Compared with the static operating revenue level, the revenue growth rate better reflects the enterprise's growth and competitiveness across different time periods and serves as a visual representation of the enterprise's output efficiency. Therefore, this study uses return on total assets and revenue growth rate as output indicators to measure the efficiency of fishery enterprises.

ESG performance is calculated using a weighted approach that synthesizes a company's performance across the three dimensions of environment, social, and governance into an overall score, thus providing an intuitive basis for comparing and ranking companies' overall performance. A high score indicates that a company performs better in environmental protection, social responsibility, and governance transparency. The ESG composite score is not only an essential measure of a company's sustainability and social responsibility but also indirectly affects its financial performance by influencing risk management, cost control, capital market attractiveness, and long-term growth potential. In this paper, ESG composite score reflects the comprehensive management capability of fishery listed companies.

Return on equity is the ratio of net profit to average net assets, reflecting a company's ability to utilize its own capital to generate net profit and is a core indicator of corporate profitability. In this paper, return on equity is used to reflect the profitability of listed fishery companies.

The asset-liability ratio is the ratio of total liabilities to total assets and reflects not only financial performance, profitability, and company value but also the enterprise's capital structure and solvency. In this paper, the asset-liability ratio is used to describe the capital structure and solvency of fishery-listed companies.

The total number of employees is the sum of a company's workforce and is an important indicator of the company's size. In this paper, the total number of employees is used to reflect the size of listed fishery companies.

Shareholding ratio of top five shareholders is used as a comprehensive indicator to reflect various aspects such as corporate governance efficiency, control distribution, financial stability, and investor confidence. In this paper, this indicator represents the decision-making efficiency and governance level of fishery listed companies.

2.3. DATA ENVELOPMENT ANALYSIS (DEA) MODELING

Data Envelopment Analysis (DEA) was proposed by Charnes in 1978, which is an efficiency assessment method based on linear programming and is widely used to measure the relative efficiency of each decision-making unit (DMU) in a multi-input and multi-output system (Wu and Zheng, 2024).[19] The basic principle of DEA is to compare the relative efficiencies of DMUs by projecting them onto a production frontier of relatively efficient DMUs while keeping each DMU's inputs and outputs constant. The method is particularly suitable for assessing decision-making units with multiple inputs and outputs and can effectively assess their production, operational, and other efficiencies. Since the inputs and outputs of listed fishery companies involve multiple dimensions and include multiple input and output indicators, it is difficult for a single indicator to comprehensively reflect their overall efficiency. DEA can handle multiple inputs and outputs simultaneously and is well-suited to this kind of complex system analysis.

Based on the scale efficiency, the basic DEA model can be divided into the CCR and BCC models. The CCR model assumes that the decision-making unit's scale efficiency remains unchanged, but in reality, the enterprise's operations are usually affected by the external environment, policies, and other factors, leading to variability in the enterprise's scale efficiency. For this reason, the BCC model emerged, and its basic assumption is that enterprise scale efficiency is variable. In the BCC model, the comprehensive technical efficiency (TE) is obtained by multiplying the pure technical efficiency (PTE) and scale efficiency (SE), with the formula: TE = PTE × SE. Given the industry environment of Chinese listed fishery companies, characterized by significant fluctuations in resource supply, policy regulation, and market conditions, they typically do not operate at constant returns to scale (i.e., the optimal production scale). Therefore, drawing on existing research, this paper selects the BCC model with variable returns to scale, whose mathematical formulas are as follows (Chen and Cheng, 2024)[20]:

$$\theta^* = \min\theta \tag{1}$$

$$s.t.\begin{cases} \sum_{n}^{j=1} x_{ij}\lambda_j \leqslant \theta_{x_{ii}} \\ \sum_{n}^{j=1} y_{\eta j}\lambda_j \geqslant y_m \\ \lambda_j \geqslant 0, \sum_{n}^{j=1}\lambda_j = 1 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n \end{cases} \tag{2}$$

Where: ,$x_{\mathrm{ij}} y_{ij}$ represents the input and output indicators, λ represents the linear combination coefficients of DMUs,$\lambda_j \geqslant 0, \sum_{n}^{j=1}\lambda_j = 1$ represents the constant returns to scale, θ^* represents the optimal solution of the model, that is, the calculated efficiency value of the model, which takes the value of [0,1], if the calculated value of the efficiency of 1, it means that the DEA is effective, and less than 1, it means that the DEA is ineffective.

Since the DEA model requires all input and output indicators to be non-negative, the data need to be normalized to dimensionless values before empirical analysis. The processing method is as follows:

$$X_n \text{ normalized } (ij) = \frac{(X_{ij} - \min_j (X_{ij}))}{\max_j (X_{ij}) - \min_j (X_{ij})} \tag{3}$$

Where $X_n normalized\ (\ ij\ )$ denotes the dimensionless value after normalization, to ensure that the data are all positive, the minimum value in each column of data is normalized and then 0.01 is added to ensure compliance with the model data requirements. $max_j(X_{ij})$ and $\min_j(X_{ij})$ denote the maximum and minimum values of the raw data, respectively.

2.4. TOBIT REGRESSION MODEL

Tobit model is a kind of econometric model used to deal with truncated or restricted dependent variables, and the core idea of the model is to solve the problem that the dependent variable may be restricted by observation when it takes values in certain ranges, for example, when the dependent variable is non-negative, and many observations are zero (Tobin, 1958).[6] The Tobit model is suitable for dealing with the case of restricted dependent variables and can provide more accurate parameter estimations. This study uses comprehensive technical efficiency (TE) of fishery listed companies as the dependent variable to analyze the factors affecting it, and the efficiency value measured by the DEA method will not exceed 1, which is restricted data, so it is suitable to use the Tobit model as a method to analyze the factors affecting the efficiency (Zhou and Li, 2012; Liu et al., 2019).[21,22]

The Tobit model is of the form:

$$y_i^* = \beta x_i + \epsilon_i, \epsilon_i \sim N\left(0, \sigma^2\right) \tag{4}$$

Where: $y_i{}^*$ is a latent variable indicating the true level at which the observations may reach; and $y_i$is the actual observation, subject to truncation, defined as:

$$y_i = \begin{cases} y_i^*, y_i^* > 0 \\ 0, y_i^* \leq 0 \end{cases} \tag{5}$$

For the linear model $y_i = x_i'\beta + \varepsilon_i$, when y_i ⩾ c (or y_i ⩽ c), all $y_{i}\ $are collapsed to c. This type of data is called "censored data". In the truncated interval, the distribution of the dependent variable Y is "compressed" into a single value; that is, all observations of the dependent variable in this region are replaced with the same value (Zhou and Li, 2012).[21] In this case, the probability distribution of y_i becomes presented as a mixed distribution consisting of a discrete point and a continuous distribution. Therefore, if the estimation is performed using ordinary least squares, the results do not provide a consistent estimate, either for the full sample or for the subsample after removing the discrete points. This is explained below:

Assume $y_i{}^* = x_i'\beta + \varepsilon_i$ ($y_i{}^*$ is unobservable) and the perturbation term $\varepsilon_i \mid x_i \sim N(0, \sigma^2)$. Without loss of generality, assume for simplicity that the subsumption point is $c = 0$. Assuming that it is observable $y_i = \begin{cases} y_i{}^*, y_i{}^* > 0 \\ 0, y_i{}^* \leq 0 \end{cases}$, the following computes the conditional expectation for the subsample $E(y_i \mid x_i; y_i > 0)$, and the conditional expectation for the whole sample $E(y_i \mid x_i)$, respectively.

For the subsample that satisfies the condition "$y_i > c$ ",

$$\begin{aligned} E(y_i|x_i; y_i > 0) = E(y_i^*|x_i; y_i > 0), \text{Given}(y_i > 0,\ \text{consequentially} y_i = y_i{}^*) \\ = E(x_i'\beta + \varepsilon_i|x_i; y_i^* > 0) \\ = x_i'\beta + E(\varepsilon_i \quad x_i; x_i'\beta + \varepsilon_i > 0 < \\ = x_i'\beta + E(\varepsilon_i \quad x_i; \varepsilon_i > -x_i'\beta) \\ = x'B + \sigma \cdot \lambda(-x'B/\sigma)(\text{Use a normally distributed tail breaker formula, and } \mathrm{E}(\varepsilon_i) = 0) \end{aligned} \tag{6}$$

Therefore, when using the subsample for regression, the OLS estimates are inconsistent because the nonlinear term $\sigma \cdot \lambda(-x_i'\beta/\sigma)$ is ignored and included in the disturbance term, resulting in the disturbance term being correlated with the explanatory variable x_i For the whole sample, the

$$\begin{aligned} E(y_i|x_i) = 0 \cdot P(y_i = 0|x_i) + E(y_i|x_i; y_i > 0) \cdot P(y_i > 0|x_i) \\ = E(y_i|x_i; y_i > 0) \cdot P(y_i > 0|x_i) \end{aligned}$$

$$\begin{aligned} thereinto, P(y_i > 0 \mid x_i) = P(y_i^* > 0 \mid x_i) = P(x_i'\beta + \varepsilon_i > 0 \mid x_i) \\ = P(\varepsilon_i > -x_i'\beta \mid x_i) = P\left(\varepsilon_i > \tfrac{-x_i'\beta}{\sigma}|\mathbf{x}_i\right) \\ = 1 - \Phi(-x_i'\beta/\sigma) = \Phi(x_i'\beta/\sigma) \end{aligned} \tag{7}$$

Thus, $E(y_i|\mathbf{x}_i) = E(y_i|\mathbf{x}_i, y_i > 0) \cdot P(y_i > 0|\mathbf{x}_i) = \Phi(\mathbf{x}_i'\beta/\sigma)[\mathbf{x}_i'\beta + \sigma \cdot \lambda(-\mathbf{x}_i'\beta/\sigma)]$ is a nonlinear function of the explanatory variable x_i. If OLS is used to tofit a linear regression on the entire sample, the nonlinear term will be included in the disturbance term, leading to inconsistent estimates.

Tobin proposed to estimate this model using MLE, and the method is therefore called "Tobit", also known as "censored regression". In the case of censored data, the probability density at $y_i > 0$ remains unchanged at $\frac{1}{\sigma}\phi[(y_i - x_i'\beta)/\sigma], \forall y_i > 0$. The distribution at $y_i \leq 0$ has been squeezed to a single point "$y_i = 0$", that is $1 - P(y_i > 0 \quad x) = 1 - \Phi(x_i'\beta/\sigma)$. Therefore, the probability density function of this mixed distribution can be written as

$$f(y_i \mid x) = [1 - \Phi(x_i'\beta/\sigma)]^{1(y_i+0)}\left[\frac{1}{\sigma}\phi((y_i - x_i'\beta)/\sigma)\right]^{1(y_i>0)} \leftarrow \tag{8}$$

Here, $1(\cdot)$ denotes the indicator function, that is, when the condition in parentheses is true, it takes the value of 1; otherwise, it takes the value of 0. From this, the likelihood function for the whole sample can be constructed, and the parameters can be estimated by maximum likelihood estimation (MLE).

However, the Tobit model is more dependent on the distributional form and therefore lacks sufficient robustness to data perturbations. If the likelihood function is not correctly specified, e.g., if the perturbation terms do not follow a normal distribution or if there is heteroskedasticity, then the QMLE estimates will be inconsistent. Intuitively, this is due to the fact that the first-order condition of MLE derived from the equation is complex.

$$f(y_i|x) = \left[1 - \Phi(x_i'\beta/\sigma)\right]^{1(y_i+0)}\left[\frac{1}{\sigma}\phi((y_i - x_i'\beta)/\sigma)\right]^{1(y_i>0)} \cdot \text{is} \cdot \text{complex.} \tag{9}$$

To overcome this limitation, a more robust method - " Censored Least Absolute Deviations " (Censored Least Absolute Deviations, abbreviated as CLAD) (Powell , 1984).The requirements of the CLAD method are limited to the perturbation term being independently and identically distributed (iid), which allows consistent estimates even when the data do not follow a normal distribution or when heteroskedasticity is present. Moreover, under certain regularity conditions, the CLAD estimates exhibit asymptotic normality. First, the normalized data model is succinctly written as

$$y_i = max(0, x_i'\beta + \varepsilon_i) \tag{10}$$

That is, if$\mathbf{y_i} = x_i'\beta + \varepsilon_i \ \ x_i'\beta + \varepsilon_i \geq 0$, then $\mathbf{y_i} = x_i'\beta + \varepsilon_i$; and vice versa $y_i = 0$. The objective function of the CLAD method is the sum of the absolute values of the deviations:

$$\min_{\beta} \sum^{i=1}_{n} \mid y_i - max(0, x_i'\beta)| \leftarrow \tag{11}$$

The CLAD estimator $\widehat{\beta}_{\text{CLAD}}$ is obtained by choosing β to minimize the sum of the absolute values of the deviations. This is actually median regression, a special case of quantile regression. The covariance matrix of $\widehat{\beta}_{\text{CLAD}}$ can be estimated by the self-help method. In summary, the results of CLAD regression analysis are finally selected in this paper.

2.5. FUZZY SET QUALITATIVE COMPARATIVE ANALYSIS (FSQCA)

Fuzzy-set Qualitative Comparative Analysis (fsQCA) is an analytical tool that combines qualitative and quantitative features, which explores multiple paths to achieve results through logical operations, and is an important method for studying complex social phenomena (Ragin, 2009).[11] This method emphasizes "configurational" thinking, which can reveal the mechanism of multiple conditional variables on the outcome variables through analyzing their different combinations, and it is especially suitable for studying the causal relationship under the interaction of multiple factors (Schneider and Wagemann, 2012).[23] From the results of Tobit model analysis, it can be seen that the input-output efficiency of fishery listed companies is affected by a variety of factors, and in real life, these different influencing factors do not affect the input-output efficiency of the enterprise in isolation, but through a certain path to jointly affect the enterprise, therefore adopting fuzzy-set qualitative comparative analysis capable of identifying the pathways of different combinations of factors on efficiency (Fiss, 2011).[24]

3. RESULTS

3.1. EFFICIENCY MEASUREMENT RESULTS

3.1.1. ANALYSIS OF INPUT-OUTPUT EFFICIENCY

In this study, Chinese A-share fishery listed companies are selected as the DMUs to analyze their input-output efficiency, and financial cost, R&D cost, shareholding ratio of major shareholders, and top three executive compensation by amount are selected as input variables; meanwhile, return on total assets and the growth rate of revenue are selected as output variables.

Based on the DEA-BCC model, this study analyzes input and output indicator data using DEAP2.1 software and calculates input-output efficiency. The results of the efficiency values are analyzed below:

TE is a comprehensive indicator for assessing the efficiency of listed fishery companies in converting resource inputs into outputs. The mean value of the companies' comprehensive technical efficiency for the period from 2019 to 2023 is 0.831, indicating a 16.9% loss in efficiency.

Table 2. Distribution of the comprehensive technical efficiency of enterprises

TE	Sample	Percentage
1	16	45.71%
0.8-1	5	14.29%
0.5-0.8	10	28.57%
0-0.5	4	11.43%

In addition, the mean scale efficiency is 0.914, while the mean PTE is 0.904, which is slightly lower than the scale efficiency. This suggests that the failure of the comprehensive efficiency to reach the optimal level (value of 1) is due to a combination of technical inefficiency and scale inefficiency, with technical inefficiency having a more significant effect. Referring to the efficiency division standard in the existing literature (Guo 2017),[25] when TE ⩾ 0.8, it indicates that the efficiency of the research object is at a high level; when 0.5 ⩽ TE < 0.8, it indicates that the efficiency of the research object is at a medium level; when TE < 0.5, it indicates that the efficiency of the research object is at a low level (Table 2).

The value of 1 for the comprehensive efficiency of firms' inputs indicates that DEA is effective in 45.71% of the total sample size, which is the largest and close to half of the total; the number of samples with a comprehensive efficiency value of between 0.8 and 1 accounts for 14.29% of the whole sample, the number of samples with a comprehensive efficiency value of between 0.5 and 0.8 has 10 sample sizes, which is 28.57% of the sample size, and there are 4 sample sizes with comprehensive efficiency values of less than 0.5, which is 11.43% of the sample size.

There may be several reasons for this phenomenon. Approximately 40% of the enterprises are experiencing diminishing returns to scale, indicating that their scale expansion has deviated from the optimal boundary of resource allocation efficiency, thereby directly contributing to losses in scale efficiency. Meanwhile, widespread deficiencies in ESG governance, such as lagging environmental technologies and extensive supply chain management, have led to a decline in pure technical efficiency. Furthermore, scale disorder exacerbates management complexity and risk exposure, further suppressing technical efficiency, while inadequate operational capabilities hinder the optimization of scale configuration. Ultimately, these interconnected factors manifest as a 16.9% loss in comprehensive technical efficiency (TE).

Pure technical efficiency (PTE) measures whether the enterprise realizes the optimal output with the given inputs without considering the SE. The average PTE of inputs for listed fishery companies is 0.904, implying an average loss of 9.6% in PTE. The specific statistical results are as follows: there are 14 samples with a PTE of 1, accounting for 40% of the total sample; there are 5 samples with a PTE between 0.8 and 1, accounting for 14.29% of the total sample; there are 3 samples with a PTE between 0.5 and 0.8, accounting for 8.57% of the total sample; and there are 3 samples with a PTE of less than 0.5, accounting for 8.57% of the total sample. Overall, the PTE values of most enterprises are close to or equal to 1, indicating that most listed fishery companies have higher technical efficiency in input use.

3.1.2. ANALYSIS OF RETURNS ON SCALE

DEA model assessment results show that there are 16 samples with SE of 1, accounting for 45.71%. SE measures how far the research object is from the optimal distance (Eder and Mahlberg, 2018),[26] an important indicator of the degree of input-output matching among DMUs. When the SE is not equal to 1, it indicates that the scale of the research object needs to be adjusted (Sergio and Daniel, 2009).[27] According to the results of the test of SE, there exist five samples that exhibit increasing scale, implying that the output of these firms grows faster than the cost inputs and should increase inputs further. On the other hand, 14 samples exhibit decreasing scale, suggesting that these firms' outputs grow more slowly, and that increases in inputs may not yield corresponding benefits (Table 3).

Approximately 40% of fishery enterprises are experiencing diminishing returns to scale, primarily attributable to three interrelated factors: input overload, inefficient management, and lagging technological efficiency. Specifically, the excessive input of traditional factors—such as aquaculture area, fishing vessel numbers, and labor, exacerbated by the scarcity of marine fishery resources and overfishing, tends to induce water pollution and increase the incidence of diseases among farmed species. Meanwhile, the proliferation of management hierarchies extends information transmission and decision-making chains, raising internal coordination costs and complicating operational governance. Furthermore, the fishery sector exhibits comparatively low technological efficiency within the agricultural subsectors and demonstrates slow technological progress, which collectively hinder enterprises from translating scale expansion into effective economies of scale

3.2. ANALYSIS OF FACTORS AFFECTING INPUT-OUTPUT EFFICIENCY

3.2.1. EXPLANATION OF VARIABLES

In this study, TE is taken as the explained variable, and five influencing factors are introduced as explanatory variables, and regressed by using Stata18.0 software. The total number of employees was logarithmically treated in order to make the model able to describe the non-linear relationship and the results more economically meaningful (Wooldridge, 2010).[28]

Table 3. Results of scale efficiency analysis

Typology	Sample	Percentage
Increasing returns to scale	5	14.29%
Diminishing returns to scale	14	40%
Constant returns to scale	16	45.71%

3.2.2. MODEL ASSUMPTIONS

ESG performance is a comprehensive evaluation indicator centered on environmental, social, and governance. Existing research has shown a positive association between firms' ESG performance and technological innovation, financial operations and management practices (Chen et al., 2024).[29] On the one hand, corporate management and technology upgrading can help promote the optimal use of input resources and minimize inputs while obtaining the same amounts of outputs, such as reducing agency costs via governance optimization (Zhang and Guo, 2024).[30] And enterprises' fulfillment of ESG responsibilities can significantly improve productivity, mainly through energy savings and resource allocation optimization (Veltri et al., 2023; Kweh et al., 2025).[31,32] On the other hand, enterprises focus on the saving and optimal allocation of input resources can help enterprises to improve the output effect through green innovation and enhancing resource acquisition efficiency through reputation and financing advantages (Kweh et al., 2025; Ma et al., 2025),[33,34] and maximize the output with the same amount of input resources (Wang et al., 2023; Gu et al., 2025).[35,36] Therefore, it can be concluded that enterprises can positively promote the improvement of input-output efficiency by improving ESG level. Based on this, H1 is proposed: the ESG composite score of fishery-listed enterprises has a positive correlation with input-output efficiency.

Return on equity is an essential financial indicator that measures the profitability and capital-use efficiency of enterprises. It has been found that a higher ROE may represent a firm's tendency to maximize short-term profits rather than optimize long-term resource allocation (Ichsani and Suhardi, 2015),[37] which in turn negatively affects input-output efficiency. This phenomenon is mainly attributed to management's excessive focus on financial performance at the expense of other key operational elements of a firm. Lozano found that in pursuit of financial performance, firms may reduce operational costs by laying off employees or cutting training costs, and that such measures may lead to a decline in labor productivity and, in turn, reduce input-output efficiency (Lozano, 2015).[38] In fisheries, a resource-intensive industry, short-term-oriented financial strategies may lead to overexploitation and resource waste, which in turn adversely affect firms' productivity. In addition, studies have shown that there is usually a conflict between maximization of shareholders' interests and long-term stakeholder value (Koberg and Longoni, 2019),[39] and an excessive focus on return on equity is not conducive to the optimization of the corporate governance structure. Friede points out that, to satisfy short-term financial objectives, firms tend to cut back on inputs related to social responsibility and environmental protection, which, in the long term, play a key role in improving the overall efficiency of enterprises (Friede et al., 2015).[15] Based on this, H2 is proposed: the return on equity of fishery listed enterprises has a negative correlation with input-output efficiency.

The asset-liability ratio is an important financial indicator that measures an enterprise's capital structure, reflecting the extent to which liabilities are used to finance total assets and is closely related to operational efficiency and financial stability. Studies have shown that bond financing can weaken the technological innovation drive of enterprises (Jiang et al., 2021),[40] which is not conducive to the improvement of productivity. According to the governance theory of corporate financing structure, debt has a strong binding effect on corporate operations (Biddle et al., 2009),[41] that is, debt financing plays a governance function to a certain extent. Based on the governance effect of debt (contract), creditors supervise and constrain the enterprise's management by entering into debt contracts to ensure debt security. As a result, creditors impose restrictions on the flow of funds to borrowing firms, and the use of funds is constrained, making it difficult for them to make high-risk investments in R&D and hampering productivity improvements and technological innovation (Smith and Warner, 1979).[42] Rajan points out that, in capital-intensive industries such as fisheries and energy, highly indebted firms are often confronted with inefficiency due to insufficient investment in technology (Rajan and Zingales, 1995).[43] There are two main reasons for this phenomenon. On the one hand, when debt levels are too high, to maintain financial stability, firms have to allocate more resources to debt repayment than to investments that enhance productivity, and this resource mismatch may hinder improvements in input-output efficiency. On the other hand, a high debt level will directly affect enterprises' operational efficiency. Firms with high debt ratios need to adopt more conservative production and operation strategies to meet debt repayment needs (Graham et al., 2015).[44] For example, enterprises may take measures to reduce inventories, lay off employees, or cut R&D costs, or prioritize short-term financial problems due to debt pressure, while neglecting improvements in long-term efficiency, reducing the efficiency of resource allocation, and thus leading to a decline in the efficiency of enterprise input and output. Based on this, H3 is proposed: the asset-liability ratio of listed fishery enterprises is negatively correlated with input-output efficiency.

The total number of employees is a proxy for the enterprise's scale, and the enterprise's scale is an important factor affecting input-output efficiency. Based on the diseconomies of scale theory (Li et al., 2023),[45] firms may enter the stage of diseconomies of scale, that is, diminishing marginal returns, when they over-expand. In this stage, scale expansion may instead hinder improvements in input-output efficiency. The potential reasons for this include higher organizational coordination costs within large firms, increased managerial complexity, and multiple challenges, such as reduced communication efficiency, distorted information transmission, and delayed decision-making. These factors work together to reduce the firm's overall operational efficiency, ultimately leading to a decline in input-output efficiency. According to the X-inefficiency theory proposed by Leibenstein, large firms lack sufficient profit-maximizing (or cost-minimizing) incentives due to relatively low competitive pressure in the external market and greater internal hierarchies and complex relationships, resulting in inefficient operations. In the Chinese A-share market, fishery listed companies occupy a large market share, and if they excessively pursue scale expansion, it may increase the management burden of the enterprise, leading to the "principal-agent" problem (Liu and Ma, 2021),[46] and exacerbate the information asymmetry, which will ultimately reduce the efficiency of the enterprise's production and management. Based on this, H4 is proposed: The scale of listed fishery firms is negatively correlated with input-output efficiency.

The shareholding ratio of the top five shareholders is an important indicator of equity concentration, with a profound impact on the governance and input-output efficiency of enterprises. In recent years, academic research has shown that higher shareholder concentration can significantly improve enterprises' input-output efficiency (Bertrand and Mullainathan, 2003).[47] According to agency theory, when large shareholders own a higher percentage of shares, they have greater incentives and ability to monitor management behavior, which can reduce agency problems, reduce management's opportunistic behavior, and solve the problem of "missing owner" (Edmans and Holderness, 2014),[48] as well as increasing the consistency of corporate decision-making through a clear strategic orientation that focuses corporate resources on high-efficiency areas (Claessens et al., 2020).[49] The governance structure of efficient firms can significantly improve the efficiency of enterprise inputs and outputs. Based on this, H5 is proposed: the shareholding ratio of the top five shareholders of listed fishery firms has a positive correlation with input-output efficiency.

Based on the above five assumptions, the Tobit regression model expression is constructed as follows:

$$Y^* = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \mu_{it}(i, t = 1, 2, \cdots, n) \quad (12)$$

Where $i$denotes the $i-th$ listed company, t denotes the time (year) β_i denotes the regression coefficient, and μ_{it} denotes the residuals; the explanatory variable Y^* represents the firm's input-output efficiency; the explanatory variable X_1 represents the firm's ESG composite score; the explanatory variable X_2 represents the firm's return on equity; the explanatory variable X_3 represents the firm's asset liability ratio; the explanatory variable X_4 represents the total number of employees in the firm (after taking logarithmic treatment); and the explanatory variable X_5 represents the shareholding ratio of top five shareholders of the firm.

3.2.3. MODEL EMPIRICAL RESULTS

Stata 18.0 software was used to calculate the data for each of the variables (Table 4).

In the CLAD regression analysis, the p-values for each explanatory variable were less than 0.01, indicating that the explanatory variables passed the 1% significance test. The study found:

The regression coefficient of ESG performance is positive and statistically significant, indicating that ESG level positively affects firms' input-output efficiency, and H1 is valid.

The regression coefficient for return on equity is negative and statistically significant, indicating that return on equity negatively affects firms' input-output efficiency, and H2 is valid.

The negative and statistically significant regression coefficient of the asset liability ratio indicates that it negatively affects the input-output efficiency of firms, and H3 is valid.

The regression coefficient for enterprise scale is negative and statistically significant, indicating that firm scale negatively affects input-output efficiency, and H4 holds.

The regression coefficient of ownership concentration is positive and statistically significant, which indicates that it positively influences the input-output efficiency of firms, and H5 is valid.

3.3. IDENTIFICATIONS OF HIGHLY EFFICIENT PATH COMBINATIONS

3.3.1. DATA CALIBRATION

Calibrating is the process of assigning cases to sets (Schneider and Wagemann, 2012; Du and Jia, 2017).[23,50] Specifically, the researcher needs to map the variables to the set based on the existing theoretical framework and case context. The calibrated set affiliation value usually lies between 0 and 1. In order to map the range of values of conditional variables between 0 and 1, researchers should combine the actual distribution of conditional variables in the case and choose calibration anchor points (full affiliation, intersection, and full non-affiliation) that accurately reflect the different degrees of conditional variables according to the actual situation (Tan et al., 2019).[51] In this study, the direct calibration method was used to convert the sample data of the outcome variable and the five condition variables into fuzzy affiliation (Ragin, 2009).[11] In selecting the anchor points, we referred to the established literature and selected the 95% and 5% quartiles of the sample data as the criteria for calibration (Andrews et al., 2016).[52] First, the 95%, 50%, and 5% quartiles were set as calibration anchors, representing the thresholds for full affiliation, intersection, and full non-affiliation, respectively (Table 5). Then, the calibration function of fsQCA was utilized to determine the affiliation of cases in these sets (Ragin, 2008),.[53]

As the fuzzy set may appear the subordinate score of 0.5, in order to avoid this situation, this paper adopts Fiss's

Table 4. Regression results of factors influencing efficiency

Variable	(1) OLS	(2) Tobit	(3) CLAD
ESG performance	0.121 (0.0922)	0.106 (0.164)	0.338*** (0.000167)
Return on equity	0.0203 (0.0161)	0.0592 (0.0387)	-0.0495*** (0.0000406)
Asset liability ratio	-0.170 (0.103)	-0.333 (0.201)	-0.194*** (0.000301)
Enterprise scale	-0.392** (0.158)	-0.575** (0.228)	-1.063*** (0.000567)
Ownership concentration	-0.793** (0.220)	-1.821*** (0.662)	0.0447*** (0.000945)
R^2	0.375	0.491	0.221

^Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01^

Table 5. Data calibration of outcome and conditional variables

Variant		Calibrations		
		Full affiliation (0.95)	Intersection point (0.5)	Full non-affiliation (0.05)
Outcome variable	TE	1	0.958	0.4025
Conditional variable	ESG performance	5.887	5.16	4.349
	Return on equity	0.8089	0.0179	-0.6498
	Asset liability ratio	0.9743	0.4913	0.2928
	Enterprise scale	3.636	3.24	2.981
	Ownership concentration	0.6189	0.4506	0.2623

method (Fiss, 2011),[24] for the occurrence of fuzzy set subordinate score of 0.5 where the condition column increased by 0.001, and at the same time to ensure that the maximum value of the fuzzy set data after the computation is not more than 1. After calculation and adjustment, the fuzzy set table for all conditional variables and the outcome variable is finally obtained.

3.3.2. NECESSITY ANALYSIS OF INDIVIDUAL CONDITION VARIABLES

The necessity of a single condition variable is to test whether the result set is a subset of a given condition set; that is, if the result occurs, then a condition variable always exists, and that condition is necessary for the result. According to the existing research, the criterion of necessity analysis is that when the consistency level is higher than 0.9, then the conditional variable can be regarded as a necessary condition for the outcome variable (Hu et al., 2024).[54] In addition, the coverage index is usually used to reflect the explanatory strength of the conditional variable on the outcome variable; when the coverage level is greater than 0.5, the explanatory strength is stronger, and the larger the value, the greater the explanatory power. The empirical results show that the consistency of the conditional variables in this study is less than 0.8 and the coverage is greater than 0.5 (Table 6), indicating that these five conditional variables have better explanatory power for the outcome variables, but none of them is a necessary condition. Therefore, there is a need to further analyze the innovation-driving effect of these combinations of conditional variables on the outcome variables.

3.3.3. SUFFICIENCY ANALYSIS OF COMBINATIONS OF CONDITIONAL VARIABLES

Sufficiency analysis of combinations of condition variables is used to test whether a grouping of multiple conditions can adequately represent a subset of outcomes; that is, to analyze how these combinations lead to the generation of an outcome (Zhang et al., 2019).[55] Specifically, a truth table of 2k rows is first constructed by fsQCA software, where k is the number of condition variables, and each row represents one possible combination of condition variables; next, combinations of condition variables that meet the requirements are filtered out by setting the frequency number and consistency threshold, where the frequency number represents the number of cases corresponding to each combination. In this study, we set the sufficient consistency threshold for grouping at 0.8, the PRI consistency threshold at 0.65, and the number of cases threshold at 1, based on Fiss's criteria as well as the general rules of QCA (Cheng et al., 2019; Charles and Larkin, 2019).[56,57] For combinations with consistency values greater than the set thresholds, the outcome variable in the column is marked as 1; otherwise, it is marked as 0 (Mendel and Korjani, 2012).[58] This method

Table 6. Results of the necessity analysis

Conditional variable	Consistency	Coverage
High ESG performance	0.61	0.72
Low ESG performance	0.59	0.65
High return on equity	0.58	0.70
Low return on equity	0.64	0.68
High asset liability ratio	0.51	0.61
Low asset liability ratio	0.66	0.71
High enterprise scale	0.51	0.61
Low enterprise scale	0.64	0.70
High ownership concentration	0.57	0.57
Low ownership concentration	0.61	0.81

ensured that the groupings retained for this study met the adequacy requirements. In our analysis, we used the intermediate solution and combined it with the parsimonious solution to distinguish between core and edge conditions. Those conditions that appeared in both the intermediate and parsimonious solutions were considered as core conditions, while those that appeared only in the intermediate solution were considered as edge conditions (Zhao and Yu, 2024).[59] Finally, five combinations of condition variables were analyzed based on these three solutions, with each column representing one combination (Table 7). Among them, boxes represent core conditions, and circles represent peripheral conditions; black boxes (■) and black circles (●) indicate the presence of the condition variable, while white boxes (□) and white circles (○) indicate the absence of the condition variable; blank spaces indicate that the condition variable may be either present or absent, representing an irrelevant condition. Core conditions are those that appear in both complex and parsimonious solutions, are essential and indispensable, and have a strong causal relationship with the outcome variable; Peripheral conditions are those that appear only in complex solutions, are substitutable, and have a weak causal relationship with the outcome variable (Sun and Li, 2021).[60]

As can be seen from Table 7, there are four kinds of enterprise input-output efficiency improvement paths, and the coverage of the overall solution is 58%, indicating that the histogram results can explain more than half of the enterprise input-output efficiency improvement paths. The consistency value of the grouping is 0.82, 0.83, 0.82, 0.89 respectively, and the consistency value of the overall solution is 0.8, all of which reach the threshold value of 0.8, which indicates that these four combinations of conditions are the sufficient conditions for the enhancement of the enterprise's input-output efficiency, and the reliability is good. Four grouping paths are explained as follows:

1. ESG-Driven. Configuration H1a indicates that, regardless of the enterprise's scale, a low return on equity, asset-liability ratio, and shareholding ratio of the top five shareholders, as long as the firm's ESG level is high, it can effectively improve its input-output efficiency. One possible reason is that enterprises with high ESG levels excel in environmental protection, social responsibility, and transparency in corporate governance. By focusing on environmental protection, energy saving, and emission reduction, enterprises can reduce resource waste and thus improve productivity; while actively fulfilling social responsibility and enhancing governance transparency can help improve management and service levels, promote the enhancement of corporate output and efficiency, and thus strengthen their input-output efficiency.
2. ESG-Scale Driven. Configuration H1b shows that, regardless of the return on equity, when a firm's asset-liability ratio and the shareholding ratio of the top five shareholders are low, a firm with a high level of ESG performance and large scale can also enhance its input-output efficiency. The reason may be that larger enterprises usually have more mature management mechanisms and greater operational experience. Compared with small-scale enterprises, large-scale enterprises usually have a longer development history, more advanced production equipment, and higher levels of production technology; therefore, large-scale enterprises with a high ESG level tend to have higher input-output efficiency.
3. ESG-Return on equity-Shareholder ownership Driven. Configuration H1c indicates that when the asset-liability ratio is low, and the firm's scale is small, the firm's input-output efficiency can be improved as long as the firm's ESG composite score is high and the return on equity and the shareholding ratio of the top five shareholders are high. The likely reason is that firms with high return on equity have strong profitability and market competitiveness, which help drive their social benefits. In addition, a higher shareholding ratio for the top five shareholders usually implies more efficient and stable strategic decision-making, which can maintain higher levels of management and ESG performance and further improve input-output efficiency.
4. Small-scale Shareholding Diversified. Configuration H2 shows that, despite differences in ROE levels, it is still possible to enhance firms' input-output effi-

Table 7. Sufficiency analysis results for combinations of conditional variables

Conditional variable	Path to improvement of input-output efficiency of enterprises			
	H1a	H1b	H1c	H2
ESG performance	■	■	■	○
Return on equity	○		●	
Asset liability ratio	□	□	□	●
Enterprise scale		●	○	□
Ownership concentration	○	○	■	□
Consistency	0.82	0.83	0.82	0.89
Raw coverage	0.34	0.31	0.22	0.30
Unique coverage	0.02	0.002	0.09	0.14
Solution consistency	0.80			
Solution coverage	0.58			

Note: ■ means the core condition exists, □ means the core condition is missing, ● means the edge condition exists, ○ means the edge condition is missing, and blank means the condition may or may not be present.

ciency with smaller scale, lower top-five shareholder shareholding ratios, and poorer ESG performance. This may be because, for small enterprises just starting out, lower top-five shareholder ownership indicates a more dispersed shareholding, a more democratized governance structure, and greater managerial autonomy. In the process of improving productivity, management is better able to listen to multiple opinions, thus avoiding arbitrary decisions by individual shareholders. In addition, small enterprises tend to be at the increasing returns to scale stage, so rational resource allocation and management can help improve their input-output efficiency.

4. DISCUSSION

4.1. RESEARCH RESULTS

This paper measures and analyzes the influencing factors of input-output efficiency of Chinese A-share fishery listed companies and identifies the high-efficiency path combinations. The main research conclusions are as follows:(1) The average comprehensive efficiency, pure technical efficiency, and scale efficiency of fishery listed companies have not reached the optimal level, and there is still potential for improvement. (2) The input-output efficiency of enterprises is influenced by many factors. ESG and ownership concentration have a positive impact on efficiency, while return on net assets, asset-liability ratio, and enterprise scale have a negative impact. Among the above influencing factors, ESG level has the greatest effect on corporate input-output efficiency, indicating that a company's environmental, social, and governance factors play an essential role in enhancing input-output efficiency. The study of Liu et al. shows that an innovative management model for an enterprise is the key to improving input-output efficiency, and the management model is an essential reflection of the operational efficiency of the enterprise (Liu et al., 2021).[61] In addition to this environment and social factors are also crucial factors, this study considers these three factors together and takes the ESG composite score as an explanatory variable, proving that it has a significant positive effect on the enhancement of firms' input-output efficiency. In addition, many scholars believe that enterprise scale has a significant effect on the input-output efficiency of environmental protection enterprises (Wang et al., 2021).[62] Different from the findings of this paper, Chiang argues that the input-output efficiency of environmental protection enterprises will expand with the expansion of enterprise scale (Chiang et al., 2004).[63] Similarly, Yu and others argue that the enterprise scale of listed coal companies positively affects their safety input-output efficiency (Yu et al., 2019).[64] This may be due to the fact that the scale of environmental protection and coal enterprises still has room for rise and improvement, while Chinese A-share fishery listed companies appear to have inefficient management, irrational resource allocation, and insufficient incentive to innovate due to their large scale, so the scale of fishery listed companies is negatively correlated with their enterprise input-output efficiencies.(3) There are four efficient driving path combinations: "ESG-Driven", "ESG-Scale Driven", "ESG-Return on equity-Shareholder ownership Driven", and "Small scale-Shareholding Diversified". Cao et al. used the super-efficient SBM model to measure the digital economic efficiency of Chinese provinces and cities and to analyze its influencing factors, and then used the fsQCA to conduct an empirical study of the multiple concurrent causality between different groupings and digital economic efficiency (Cao et al., 2024).[65] Xie used the DEA-BCC model to calculate technical efficiency performance and its distribution in Chinese ports, and then used fsQCA to integrate and analyze the influencing factors (Xie and Hu, 2024).[66] Although existing studies have combined DEA and fsQCA to explore the enhancement paths of various types of efficiency, the application of this methodological combination in the fishery field remains relatively limited. This paper systematically analyzes the driving factors behind the high input-output efficiency of listed fishery companies, thereby expanding research perspectives in this field.

Based on the strategic perspective of the sustainable utilization of global fishery resources, this study constructs an input-output efficiency evaluation system for fishery-listed companies on China's A-share market. It fills a gap in systematic research on the operational efficiency of fishery enterprises in developing countries and provides empirical evidence for research on the global fishery economy in emerging market countries. This paper conducts an in-depth analysis of the current efficiency situation of fishery-listed companies and the factors influencing it. From a group-based perspective, it identifies four efficiency-driving paths and addresses the core question posed in the introduction: "how can fishery enterprises achieve high efficiency and sustainable development under resource constraints". This study holds practical significance for the formulation of fishery policies and the sustainable and healthy development of the aquatic products industry.

4.2. PRACTICAL INSIGHTS

1. As typical representatives in the agricultural sector, listed fishery companies have industry-referential value in their efficiency enhancement paths, which can provide empirical evidence for improving the efficiency and financial performance of enterprises in other agricultural sectors. For large-scale enterprises, enhancing ESG performance and ownership concentration is conducive to improving input-output efficiency; for small-scale enterprises, ownership diversification is more effective in promoting efficiency improvement. Therefore, enterprises should optimize their management, adjust ownership structures in light of their own characteristics, and enhance core competitiveness by improving input-output efficiency to achieve sustainable development.
2. Affected by corporate governance and market complexity, the driving factors of enterprises' input-output efficiency present a diversified feature. In a complex market environment, a single factor is hardly sufficient to significantly improve overall efficiency, so enterprises need to attach importance to the synergistic paths of multiple factors.
3. ESG performance is crucial for enterprises to improve efficiency. At the corporate level, enterprises are encouraged to establish ESG performance evaluation mechanisms and optimize equity incentive schemes. Enterprises should improve environmental quality by implementing energy conservation, emission reduction, and resource recycling; fulfill social responsibilities by safeguarding employees' rights and interests and participating in community development; and enhance management capabilities by improving governance structures and information disclosure systems. At the governmental level, authorities are urged to enhance ESG disclosure standards and increase green subsidies for the fisheries sector.

4.3. SHORTCOMINGS AND FUTURE PROSPECTS OF THE STUDY

This study suffers from the following shortcomings: first, the research sample is limited to Chinese A-share fishery listed companies, which may impose some limitations on the generalizability of the findings; second, although the DEA model is suitable for efficiency assessment, it has some limitations in considering environmental and external conditions; third, the identification results of the fsQCA for paths depend on variable calibration and data quality, which may be affected by subjectivity bias.

Future research can be carried out in the following ways: first, expand the sample scope to cover fishery firms in more countries or regions to further enhance the applicability and generalizability of the findings; second, introduce a dynamic efficiency analysis model to examine the dynamic characteristics of efficiency over time; third, combine multidimensional data sources, such as environmental monitoring data and social responsibility reports, to further reveal the long-term impact of ESG composite score on efficiency; fourth, exploring a more detailed classification of firm characteristics to deepen the understanding of differentiated efficiency paths for fishery firms.

AUTHORS' CONTRIBUTIONS

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