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# A Study on the Efficiency of Green Technology Innovation in Listed Chinese Water Environment Treatment Companies

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**Abstract:** With the continuous advancement of the economy, the issues of resource scarcity and environmental damage are becoming increasingly severe. For example, in terms of water resources, the problems of environmental pollution and ecological imbalance in the water caused by industrial and agricultural wastewater are becoming more serious. In order to reduce water pollution, protect water resources, promote ecological balance, and reduce environmental risks, it is necessary to strengthen water environment management. This study uses the Malmquist DEA model to conduct a study on the green technology innovation efficiency (GTIE) of 24 water environment governance companies from 2019 to 2022. Corporate Research & Development investment and employee compensation are used as the input indicators, while the number of color patents obtained and operating income are employed as the output indicators. The evaluation criteria include pure technical efficiency, comprehensive technical efficiency, scale efficiency, and total factor productivity. The results show that there is significant room for improvement in the GTIE of the listed Chinese water environment governance enterprises, and there are considerable differences among different enterprises. The GTIE is significantly influenced by technological progress, the enterprise size, and the equity ratio. Therefore, water environment management enterprises should enhance their efforts in technological research and development and talent training, optimize resource allocation, improve the efficiency of green technology innovation, and effectively fulfill their social responsibilities. These measures will promote the efficient utilization of ecological water, the restoration of the water environment, and the establishment of a clean ecological environment.

**Keywords:** water environment management; green technology innovation; Malmquist DEA; total factor productivity

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## 1. Introduction

In the 20th century, rapid economic growth and population expansion led to a substantial increase in human consumption of natural resources and consequent environmental damage. Among these issues, water scarcity and pollution have become particularly prominent. The discharge of wastewater from industrial, agricultural, and domestic activities has put significant pressure on water ecosystems, resulting in a growing scarcity of water resources and severe disruptions to water ecology. The importance of water environment governance at a global scale has increased in response to this significant challenge. Taking my country as an example, the urgent need for water environment management is further exacerbated by its large population and uneven distribution of water resources [1].

Green technology is widely recognized as a solution to this problem. It refers to the utilization of advanced scientific and technological innovations that are based on ecological principles and sustainable development concepts. Its primary objectives are to optimize resource utilization, protect the environment, and restore ecological balance [2]. Green technology is a type of technology that takes into account resource and environmental limitations, fulfills corporate social responsibility obligations, and demonstrates effectiveness through innovation. For companies engaged in green technology research and development, the adoption of green technology can bring both environmental and economic benefits [3]. By employing environmentally friendly technology, businesses can enhance their productivity and the quality of their output while reducing their expenses. Furthermore, they can integrate their supply chain at a broader level, leading to the most efficient allocation of resources. This integration can also facilitate the transformation, modernization, and advancement of traditional industries, while strengthening the technological innovation capabilities of industrial companies through digital economic empowerment, thereby enhancing the international competitiveness of these industries. This is also known as green technology innovation efficiency (GTIE). In recent years, there has been increasing interest in both academic and commercial circles in evaluating the effectiveness of green technology innovation in industrial organizations [4].

Green technological innovation possesses both social characteristics, such as environmental protection, energy conservation, and emission reduction, and economic characteristics, including enhancing enterprise production efficiency and competitiveness. This enables it to effectively address the dilemma between economic development and environmental protection [5]. In terms of assessing the efficiency of green technology innovation, the mainstream methods in the academic community can be categorized into two groups: parametric methods, such as the stochastic frontier approach (SFA), and non-parametric methods, such as data envelopment analysis (DEA). For instance, Li et al. measured China's green innovation efficiency and examined the coupling coordination degree between its green innovation efficiency and ecological welfare performance using a coupling coordination degree model [6]. Jiang et al. evaluated the technical efficiency levels across different regions in China and analyzed their changing trends [7]. Zhang et al. utilized the SFA model to individually measure and analyze the two main components of green technology innovation efficiency, namely technological change and technical efficiency, in 33 countries along the "One Belt and One Road" initiative [8]. However, the SFA method requires the formulation of hypotheses in advance and cannot simultaneously link positive and negative outputs. This study addresses this limitation by incorporating the distance function (DDF) to capture the hindering effect of market factor mismatch. Du et al. analyzed the efficiency of green technology innovation in China's industrial enterprises in 2014 using DEA models [9]. Their findings reveal that the nationwide technological innovation efficiency has improved, with the highest efficiency observed in the eastern region. Guan et al. focused on industrial enterprises as their research subject and employed a two-stage DEA model to empirically test green technology innovation efficiency [10]. The results highlighted significant variations in efficiency between provinces and regions, indicating the need for improvement. Nasie et al. examined the impact of financial investment and environmental regulations on corporate green technology innovation efficiency using the DEA-Tobit model [11]. They concluded that government actions do not significantly promote positive advancements in corporate green technology. Scholars generally favor the DEA model for calculation methods [12]. For instance, Nasierowski et al. [13] employed the DEA method to quantify green innovation efficiency and examined the outcomes of investment in green innovation processes and their efficiency in 2005 and 2009.

However, while there have been some studies focusing on green technology development, there is a lack of research specifically addressing water environmental regulation. Moreover, many of the existing studies primarily focus on the theoretical aspects and lack practical implementation and efficiency assessments [14]. Additionally, the endogenous logic in several empirical studies has not been fully demonstrated, leading to the low credibility of the conclusions. Our current understanding of the influencing mechanisms for corporate technological innovation is still incomplete. Therefore, this study aims to fill this gap by focusing on the water governance sector in China and utilizing the Malmquist

DEA methodology to examine the efficiency of listed water governance companies and the factors influencing their efficiency.

This study focuses on the regulation of the water environment and also evaluates the efficiency of green technology innovation (GTIE) from a new perspective. The aim of this research is to assess how effective GTIE is in water environment management enterprises in our country. The sample for this assessment consists of publicly listed companies in the water management industry. The study primarily examines the relationship between GTIE and various characteristics, such as Research & Development investment and other financial indicators. This research is unique compared to previous studies, as it introduces a novel research subject. Previous studies on corporate innovation efficiency have typically focused on either an entire listed company or an entire city, rather than concentrating on a specific industry. In the traditional research, the focus of the GTIE index has mainly been on the new energy sector, with firms in high-tech industries taking precedence and manufacturing being a secondary component. There has been a lack of research in the water environment management industry. Furthermore, previous research has primarily concentrated on the treatment efficiency of domestic municipal or standard sewage treatment plants, overlooking the examination of water treatment enterprises with corporate organizational structures. Given the broad scope of the research subject, this article primarily evaluates the efficiency of green technology innovation in water treatment firms and its determining factors. Additionally, it explores the reasons for the significant variations observed across different organizations over different years. In the face of significant environmental challenges and emerging economic development scenarios, the adoption of green technology is essential for organizations to ensure their long-term sustainability. Prioritizing technical innovation is crucial for achieving transformation and development more effectively. By measuring and researching the GTIE of firms at the micro-level, more precise management models and strategies to enhance GTIE can be developed.

## 2. Modeling and Data Processing

### 2.1. Research Methodology

This article employs the data envelopment analysis (DEA) method of frontier analysis, utilizing the DEA-SOLVER Pro5.0 made by Cabit Information Technology Co., Ltd. in China to calculate the GTIE (Green Technology Innovation Efficiency) of 24 A-share listed water environment treatment enterprises. This is achieved by assessing how much different enterprises deviate from the efficiency frontier enterprises. A firm's efficiency can be quantified by measuring the degree of deviation. A higher degree of deviation results in a lower GTIE value, while a smaller degree of deviation leads to a higher GTIE value. A higher GTIE is associated with a reduced degree of variance in the firm [15]. Frontier analysis includes parametric and non-parametric methods. The parametric method requires assuming the frontier function when calculating the efficiency, and one of the most commonly used calculation models is the stochastic frontier approach (SFA). The non-parametric method does not require assuming the frontier function when calculating the efficiency, and one of the most commonly used calculation methods is data envelopment analysis. This paper selects the DEA model, a non-parametric method, to measure the efficiency of investment and asset allocation in enterprises in the water environment management industry. The DEA model is chosen because it can consider multiple input and output indicators without the need to weight each indicator. It also evaluates from the perspective most favorable to the decision-making unit, measuring the allocation efficiency.

In this paper, each enterprise in the water environment management industry is treated as a decision-making unit (DMU). The DEA method is utilized to construct the frontier surface, and each enterprise is compared against this frontier surface to measure its GTIE [16].

The basic DEA model is founded on two key assumptions: constant returns to scale (CRS) and variable returns to scale (VRS). The CRS model is utilized to evaluate the efficiency of the decision-making units (DMU) by assuming that the returns to scale of each

DMU remain constant. This means that when a DMU increases its input, its output increases according to the same proportion that the input increases. The CRS model is often employed to measure the technical efficiency (TECH) of a DMU, which indicates the maximum output that can be obtained with a given input. Using the CRS model, the relative efficiency and production possibility frontier of a DMU can be assessed in order to optimize its resource allocation and production process. On the other hand, VRS is another assumption in the DEA model that is opposite to CRS and postulates variable returns to scale. In the VRS model, when a DMU increases its input, the increase in output may not necessarily be proportional to the input increase. "The CCR model" is also a common name for the CRS model. The VRS model is commonly used to evaluate the pure technical efficiency (PTECH) of a decision-making unit (DMU). It reflects the maximum achievable output given the input and a specific production scale. Using the VRS model, the efficiency performance of a DMU can be assessed under different production scales, enabling further analysis of the optimization potential in its production process and resource allocation. These two models, CRS and VRS, are utilized within the DEA framework to evaluate the efficiency of a DMU and the different aspects of its production process. The CRS model primarily focuses on assessing its technical efficiency, while the VRS model specifically evaluates its pure technical efficiency and considers the impact of the production scale on efficiency. In the DEA model, the CCR (Charnes, Cooper, and Rhodes) model measures efficiency under the assumption of constant returns to scale, while the BCC (Banker, Charnes, and Cooper) model measures efficiency under the assumption of variable returns to scale. Compared to the CCR model, the BCC model includes an additional equality constraint ($\sum\lambda = 1$) to account for variable returns to scale. The CCR model provides a measure of comprehensive technical efficiency, which indicates the optimal state of resource allocation, technology application, and production efficiency for the decision-making unit. A crste value of 1 signifies that the unit has achieved the highest level of comprehensive technical efficiency, while a crste value less than 1 suggests room for improvement. On the other hand, the BCC model evaluates pure technical efficiency, which assesses the efficient use of input resources at the current technical level. If vrste equals 1, this implies that the production unit is utilizing its input resources efficiently. However, if vrste is less than 1, this indicates that there is still potential for improvement. Additionally, the scale efficiency (scale) can be obtained by dividing the crste value by the vrste value.

In the DEA model calculations, there are n decision-making units (DMUs). The inputs and outputs of the ith DMU are represented by x and y, respectively. The efficiency value of each DMU is measured using the CCR and BCC modeling formulas.

The CCR model with non-Archimedean infinitesimal ε is:

$$\text{s.t.}\begin{cases} \min\left[\theta - \varepsilon\left(\hat{e}^{T}s^{-} + e^{T}s^{+}\right)\right] = V_{D}(\varepsilon) \\ \sum_{i=1}^{n} x_i\lambda_i + s^{-} = \theta x_{i0} \\ \sum_{i=1}^{n} y_i\lambda_i - s^{+} = y_{i0} \\ \lambda_i \geq 0, i = 1, 2, \ldots, n \\ s^{-} \geq 0, s^{+} \geq 0 \end{cases} \tag{1}$$

The BCC model with non-Archimedean infinitesimal ε is:

$$s.t.\begin{cases} min\left[\theta - \varepsilon\left(\hat{e}^{T}s^{-} + e^{T}s^{+}\right)\right] = V_{D}(\varepsilon) \\ \sum_{i=1}^{n} x_i\lambda_i + s^{-} = \theta x_{i0} \\ \sum_{i=1}^{n} y_i\lambda_i - s^{+} = y_{i0} \\ \sum_{i=i}^{n} \lambda_i = 1 \\ \lambda_i \geq 0, i = 1, 2, \ldots, n \\ s^{-} \geq 0, s^{+} \geq 0 \end{cases} \tag{2}$$

The DEA model is essentially a linear programming problem, where DMUs are denoted by i = 1, 2, . . ., n, and x and y represent the input and output vectors, respectively. The weight of the ith DMU, $\lambda_i$, is determined when the $ith_0$ DMU is efficient, and $e$ denotes the slack vector. $\varepsilon$ is a non-Archimedean infinitesimal quantity, while θ signifies the efficiency value of the ith DMU. The efficiency value of the DEA model ranges between 0 and 1, with 1 indicating perfect efficiency. Additionally, $s^+$ and $s^-$ are the slack variables, i.e., the difference between the actual and target values of the inputs and outputs. The expression of the slack variables can be defined as follows:

$$S_{k,i} = x_{k,i} - \sum_{k=1}^{K} \lambda_i x_{k,i} \tag{3}$$

where $k$ = 1, 2, . . ., $K$, $i$ = 1, 2, . . ., $n$. $S_{k,i}$ denotes the kth input slack of the $i$th DMU.

If $\theta = 1, S^+ = S^- = 0$, then the decision-making unit DEA is valid.

If $\theta < 1$, then the decision-making unit non-DEA is valid.

The objective of this study is to assess the trend in the GTIE among 24 A-share listed companies in the water environment governance industry. To achieve this goal, we utilize the Malmquist index model within the DEA framework to calculate the dynamic efficiency of China's listed companies operating in the water environment governance sector. The Malmquist index model is expressed as follows. Table 1 is a list of variable definitions for Equation (4).

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \left[ \frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \tag{4}$$

**Table 1.** List of variable definitions for Equation (4).

| Variable Name | Variable Definition |
| --- | --- |
| M | Malmquist productivity change index |
| $D^t$ | The distance function of the decision-making unit (DMU) in period t using the technology from period t as the reference technology |
| $x_t$ | The input quantities in period t |
| $y_t$ | The output quantities in period t |

Sources of Data

For the purpose of this research, the sample selection focused on companies whose major business activities are related to "water treatment" and "water treatment" only. Additionally, listed samples from 2019 onward were eliminated to ensure an uninterrupted and efficient data flow. After extensive treatment, this paper focused on the data extracted on 24 publicly traded firms between 2019 and 2022. The primary sources of data collection and organization include the China Statistics Yearbook and the WIND databases.

To facilitate clarity and analysis, this paper assigns names to the 24 firms as A1 through A24 in Table 2.

**Table 2.** Names, stock codes, and the corresponding coding numbers.

| Stock Code | Firm Name | Code Serial Number |
| --- | --- | --- |
| 544 | Zhongyuan environmental protection | A1 |
| 598 | Xingrong environment | A2 |
| 605 | Bohai stock | A3 |
| 685 | Zhongshan public | A4 |
| 2573 | Fresh environment | A5 |
| 300055 | Wanbangda | A6 |
| 300070 | Bishuiyuan | A7 |
| 300172 | Zhongdian environmental protection | A8 |
| 300262 | Baan water | A9 |

**Table 2.** *Cont.*

| Stock Code | Firm Name | Code Serial Number |
|---|---|---|
| 300266 | Xingyuan environment | A10 |
| 300334 | Jinmo technology | A11 |
| 300388 | Energy-saving guozhen | A12 |
| 300422 | Boshiko | A13 |
| 300437 | Qingshuiyuan | A14 |
| 300664 | Pengyao environmental protection | A15 |
| 300692 | Zhonghuan environmental protection | A16 |
| 600008 | Shouchuang environmental protection | A17 |
| 600461 | Hongcheng environment | A18 |
| 600874 | Entrepreneurship and environmental protection | A19 |
| 601158 | Chongqing water affairs | A20 |
| 603200 | Shanghai Xiba | A21 |
| 603603 | T botian | A22 |
| 603817 | Strait environmental protection | A23 |
| 603903 | Zhongzhi shares | A24 |

### *2.2. Indicator Selection*

This study focuses on the GTIE of 24 Chinese water environment governance companies. The article will specifically address the data related to the input and output indices, which are displayed in Table 1 with precise measurement indicators.

Research and development expenditure: Enhancing the productivity and innovation efficiency of manufacturing firms is primarily focused on product innovation. Capital investment is crucial for any technological innovation and development. Therefore, this article chooses to use R&D investment as a metric for capital investment, emphasizing the company's expenditure on research and development.

Allocation of human resources: To achieve green innovation, enterprises must rely on talent development to carry out technology research and development. Investing in personnel has a positive impact on the performance of green innovation. Offering competitive salaries to employees is an effective method for incentivizing and inspiring talented individuals. Hence, the indicators for investment in human resources are chosen based on employees' remuneration.

Economic gains generated: Business revenue refers to the economic benefits generated by firms and is considered an indirect result of innovation in green technology. Therefore, the magnitude of financial advantages for businesses is assessed using operational income metrics.

The outcome of innovative findings in green technology: The advancement of the technology market is crucial for fostering autonomous innovation and facilitating the conversion of technical breakthroughs. The intermediate output of corporate innovation activities is influenced by the acquisition or authorization of green patents. To accurately demonstrate the immediate outcomes of green innovation endeavors, efficient green invention patents are acquired as a result of technological innovation.

The variable definitions are shown in Table 3.

**Table 3.** Evaluation of the GTIE index system.

| | Indicator Name | Symbol | Unit |
|---|---|---|---|
| Input indicator | R&D investment | X1 | billion |
| | Employee compensation | X2 | billion |

**Table 3.** *Cont.*

| | Indicator Name | Symbol | Unit |
|---|---|---|---|
| Output indicator | The number of color patents obtained | Y1 | / |
| | Operating income | Y2 | billion |

## 3. Analysis of the Results

This article employs the DEA-SOLVER Pro5.0 made by Cabit Information Technology Co., Ltd. in China to compute the BCC model with variable returns to scale. It selects input orientation optimization with fixed output to calculate the GTIE of 24 A-share listed enterprises in the water environment treatment industry, resulting in the GTIE values for each enterprise, as shown in Table 4.

**Table 4.** GTIE of enterprises in the water environment treatment industry, from 2019 to 2022.

| Short Form | Combined Technical Efficiency | Pure Technical Efficiency | Scale Efficiency | Scale Gains |
|---|---|---|---|---|
| A1 | 0.570 | 0.834 | 0.705 | drs |
| A2 | 0.988 | 0.992 | 0.995 | irs |
| A3 | 1 | 1 | 1 | - |
| A4 | 0.221 | 0.270 | 0.821 | drs |
| A5 | 0.450 | 0.995 | 0.452 | drs |
| A6 | 0.657 | 0.759 | 0.856 | drs |
| A7 | 0.680 | 1 | 0.680 | drs |
| A8 | 1 | 1 | 1 | - |
| A9 | 0.668 | 0.758 | 0.869 | irs |
| A10 | 0.500 | 0.557 | 0.891 | drs |
| A11 | 0.561 | 0.607 | 0.920 | irs |
| A12 | 0.802 | 0.959 | 0.833 | drs |
| A13 | 0.448 | 0.741 | 0.661 | drs |
| A14 | 0.727 | 0.748 | 0.965 | drs |
| A15 | 0.745 | 0.754 | 0.987 | drs |
| A16 | 0.573 | 0.761 | 0.757 | irs |
| A17 | 0.803 | 1 | 0.803 | drs |
| A18 | 0.614 | 0.909 | 0.682 | drs |
| A19 | 0.759 | 0.864 | 0.867 | drs |
| A20 | 0.970 | 1 | 0.970 | - |
| A21 | 0.584 | 0.805 | 0.686 | irs |
| A22 | 0.451 | 0.607 | 0.762 | - |
| A23 | 0.578 | 0.858 | 0.701 | drs |
| A24 | 0.780 | 0.792 | 0.977 | drs |
| mean | 0.672 | 0.815 | 0.827 | |

In Table 4, EFFCH represents the combined technical efficiency, which indicates how close the decision-making unit is to the optimal production boundary or technological frontier. The greater the technical efficiency, the closer the decision-making unit is to the optimal production boundary, and the higher its efficiency. EFFCH can be further decomposed into pure technical efficiency (PECH) and scale efficiency (SECH). TECHCH represents technological progress, which refers to the outward shift of the technological frontier and the maximum output increase under the current technological level. PECH represents pure technical efficiency, which takes into account factors like corporate management and technology that affect the production efficiency. SECH represents the scale efficiency, which represents the production efficiency as it is affected by the enterprise's size. TFPCH represents the total factor productivity change and is calculated as TFPCH = TECHCH * EFFCH. The EFFCH value can also be decomposed into pure technical efficiency changes

(PECH) and scale efficiency changes (SECH). Unlike the comprehensive technical efficiency index, the Malmquist DEA index model reflects dynamic changes in efficiency, and the EFFCH represents the change in efficiency caused by changes in the relative efficiency.

The average EFFCH value of the 24 water environment governance enterprises as a whole between 2019 and 2022 is below 0.8, specifically 0.672, indicating a low overall GTIE. The ability to convert R&D inputs into technological innovation outputs is poor, highlighting the need for improvement in the overall GTIE of these enterprises. There is significant room for enhancement in their overall GTIE. On the other hand, the mean PECH value of these enterprises over the four-year period is 0.815, indicating a good resource allocation capacity and management level in terms of GTIE inputs and outputs. Furthermore, the mean SECH value is 0.827, suggesting that the 24 water environment treatment enterprises as a whole have a reasonable development scale in green technology innovation. However, the mean PECH value is lower than the mean SECH value, indicating that the low PECH is the primary reason for the low EFFCH. This implies that the water environment management enterprises should prioritize improving their resource allocation capacity and management level (PECH) to effectively enhance their own GTIE.

Considering the average EFFCH values for each enterprise in the water environment management sector, it is apparent that there are significant efficiency differences among the 24 enterprises. The average EFFCH falls between 0.221 and 1, indicating varying levels of efficiency. Out of the 24 enterprises, 11 have an EFFCH higher than the overall average level. Additionally, six enterprises (A3, A8, A2, A20, A17, and A12) have an average EFFCH exceeding 0.8. These enterprises, especially A3 and A8, consistently maintained an EFFCH value of 1 between 2019 and 2022, establishing themselves as benchmark entities in the water environment management sector. The higher mean EFFCH suggests that these enterprises possess a high level of general technical and innovative efficiency (GTIE). On the other hand, 10 out of the 24 enterprises have an average EFFCH below 0.6 (A21, A23, A16, A1, A11, A10, A22, A5, A13, and A4). Among them, four enterprises (A22, A5, A13, and A4) exhibit a comprehensive technical efficiency index below 0.5. The lower average EFFCH values indicate a poor GTIE for these 10 enterprises, which hampers industry-wide efficiency improvement.

The PECH values of the 24 water environment management enterprises range from 0.27 to 1, indicating significant disparities in the resource allocation capability for green technological innovation among the enterprises. Out of the 24 enterprises, 13 have a PECH value higher than 0.8. Moreover, five enterprises (A3, A8, A20, A17, and A7) exhibit a PECH average value of 1 between 2019 and 2022, indicating consistently high levels of resource allocation capability and management proficiency. These enterprises possess robust resource allocation capabilities, facilitating their efficiency in green technology innovation. On the other hand, the mean value of PECH for the 24 enterprises, including A4 and A10, is lower than 0.6, suggesting a poorer resource allocation ability and low management levels for green technological innovation. These enterprises fail to transform R&D investment into green technology innovation output effectively.

From the perspective of SECH, the mean value of SECH for the 24 water environment management enterprises falls between 0.452 and 1, surpassing the mean value of PECH, which represents the minimum land efficiency value for enterprises, indicating a superior performance compared to PECH. A total of 15 of the enterprises exhibit a scale efficiency mean value exceeding 0.8, suggesting that the collective scale development of the 24 enterprises in green technology innovation is favorable. However, the scale efficiency of one enterprise, A5, is below 0.6, indicating that its development scale in green technology innovation is unreasonable, thus impeding the enhancement of its GTIE.

Based on the EFFCH decomposition results mentioned above, out of the 24 enterprises, there are 11 whose scale efficiency is lower than their PECH. These enterprises are A5, A13, A7, A18, A21, A23, A1, A16, A17, A12, and A20. Among these, the average PECH of A5 is higher than the scale efficiency by 0.5. The SECH of these 11 enterprises is lower than their PECH, indicating that the main hindrance to the development of GTIE in these enterprises is low scale efficiency, which means their scale is not optimal. Therefore, these enterprises need to make timely adjustments to their development scale based on their own characteristics and environmental changes in order to effectively enhance their innovation efficiency. In addition to A3 and A8, which have the highest PECH and SECH values, the other types of enterprises (11 in total) have higher SECH values than PECH values. These enterprises are A22, A4, A6, A19, A9, A10, A11, A14, A24, A15, and A2. Compared to scale efficiency, the main reason for the low EFFCH in these types of enterprises is a low PECH, indicating an insufficient resource allocation capacity and a low management level. According to the data results, it is clear that the number of patent applications from water environment treatment firms has significantly increased in recent years. However, the conversion rate of these applications is notably low, limiting the impact on improving their innovation efficiency. To address this issue, enterprises need to adapt to ever-changing market demands by focusing on specific segments of innovation and research and development. This will enable them to develop core technologies and continuously enhance their practical application, thereby creating a distinct competitive advantage. In particular, digital applications play a crucial role in fostering innovation and improving efficiency. Through the utilization of digital information technology, enterprises can automatically collect data on water quality indicators, flow rates, water temperature, and more. By employing machine learning and big data analysis techniques, real-time monitoring of the water environment becomes possible, enabling the prediction of future trends and supporting decision-making processes. Furthermore, artificial intelligence can be utilized to analyze the water treatment process parameters and identify the optimal treatment conditions using optimization algorithms. This approach enhances the water treatment efficiency and effectiveness while reducing energy and resource consumption [17].

Among the 24 enterprises, A21, A16, A9, A11, and A25 exhibit increasing returns to scale, indicating that allocating more resources for research and development will lead to a greater production of environmentally friendly technological advancements. This suggests a growing market demand for eco-friendly innovations. However, these firms face challenges in meeting this demand due to limitations in their current input and output capacities. On the other hand, A22, A20, A3, and A84 enterprises show no change in returns to scale, with A3 and A84 demonstrating constant returns to scale. This implies that increasing R&D inputs will proportionally increase the technological innovation output. The remaining 15 enterprises exhibit diminishing returns to scale, which means that blindly increasing their R&D investment may lead to a decline in the efficiency of their green technological innovation.

In the model construction and analysis above, corporate governance and internal governance models evidently have a significant impact on firms' R&D efficiency and effectiveness. Both too small and too large of a scale can affect the improvement of the innovation efficiency [18]. Therefore, enterprises should enhance their resource allocation capacity and establish a reasonable enterprise scale and internal management mechanism. They should also optimize shareholders' equity structure and the organizational scale. Water environment governance enterprises need to reassess their organizational scale and management mechanisms to ensure that all production factors can maximize their benefits. Furthermore, they should adhere to market-demand-oriented strategies and optimize investment into and the allocation of funds, technology, talents, and other resources [19]. Additionally, in the context of carbon reduction efforts, water environment governance enterprises need to upgrade their operational capabilities in two key areas: (1) the ability to conserve energy and minimize consumption to achieve low carbon and low energy consumption; (2) the ability for intelligent operation. For heavy-asset enterprises involved in water governance, improving the intelligent asset operation efficiency and optimizing the investment of funds into appropriate areas and technological research and development are essential.

Table 4 exclusively focuses on static efficiency and neglects analysis of the dynamic perspective regarding the GTIE of each enterprise. Hence, this research utilizes the DEAP2.1

software to calculate and assess the total factor productivity index of 24 companies from 2019 to 2022, considering both dynamic-level and development trends, using the Malmquist index model. The findings are displayed in Tables 5 and 6.

**Table 5.** Overall total factor productivity index and its decomposition for 24 firms.

| Year | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 2019–2020 | 0.877 | 1.342 | 0.927 | 0.946 | 1.178 |
| 2020–2021 | 1.133 | 0.876 | 1.005 | 1.128 | 0.993 |
| 2021–2022 | 0.685 | 1.333 | 0.815 | 0.84 | 0.913 |
| mean | 0.88 | 1.162 | 0.912 | 0.964 | 1.022 |

**Table 6.** Total factor productivity and its decomposition by firms, from 2019 to 2022.

| DMU | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| A1 | 0.829 | 1.319 | 1.048 | 0.791 | 1.093 |
| A2 | 0.983 | 0.885 | 0.99 | 0.994 | 0.87 |
| A3 | 1 | 1.311 | 1 | 1 | 1.311 |
| A4 | 0.871 | 1.064 | 0.959 | 0.909 | 0.927 |
| A5 | 0.944 | 1.199 | 1 | 0.944 | 1.132 |
| A6 | 0.76 | 1.265 | 0.817 | 0.929 | 0.961 |
| A7 | 0.986 | 1.182 | 1 | 0.986 | 1.165 |
| A8 | 1 | 1.062 | 1 | 1 | 1.062 |
| A9 | 0.93 | 1.105 | 0.936 | 0.994 | 1.028 |
| A10 | 1.054 | 1.218 | 1.005 | 1.048 | 1.284 |
| A11 | 1.062 | 1.228 | 0.968 | 1.097 | 1.305 |
| A12 | 0.989 | 1.152 | 1.008 | 0.982 | 1.14 |
| A13 | 0.696 | 1.252 | 0.651 | 1.069 | 0.871 |
| A14 | 0.783 | 1.302 | 0.803 | 0.975 | 1.02 |
| A15 | 0.814 | 1.155 | 0.816 | 0.998 | 0.941 |
| A16 | 0.835 | 1.254 | 0.718 | 1.162 | 1.047 |
| A17 | 0.759 | 1.063 | 1 | 0.759 | 0.807 |
| A18 | 0.812 | 1.166 | 1.065 | 0.762 | 0.947 |
| A19 | 0.833 | 1.124 | 1.012 | 0.823 | 0.936 |
| A20 | 1.044 | 1.025 | 1 | 1.044 | 1.07 |
| A21 | 0.562 | 1.064 | 0.778 | 0.722 | 0.598 |
| A22 | 0.808 | 1.175 | 0.758 | 1.066 | 0.95 |
| A23 | 1.119 | 1.226 | 0.855 | 1.309 | 1.371 |
| A24 | 0.886 | 1.197 | 0.89 | 0.995 | 1.06 |
| mean | 0.88 | 1.162 | 0.912 | 0.964 | 1.022 |

The TFPCH in the results represents the full factor productivity, which reflects the effectiveness of changes in production and operation over time. It quantifies the total output of each unit or the ratio of total output to all factors input. As shown in Table 4, the mean value of the total factor productivity index for the 24 enterprises in green technological innovation from 2019 to 2022 is 1.022, indicating an upward trend in the 4-year period with a 2.2% increase. This suggests that the efficiency of the 24 enterprises as a whole in green technological innovation has improved. The decomposition of the total factor productivity index shows that the mean value of the technical efficiency change index is 0.88, indicating a 12% decrease in the technical efficiency change index for the 24 enterprises as a whole. Furthermore, the mean value of the technical progress index is 1.162, indicating a 16.2% increase in the technical progress index. This underscores that the improvement in technical progress serves as the primary driving force behind the enhancement of the total factor productivity index.

Analyzing the total factor productivity index for each time period, the index for the four-year period from 2019 to 2022 demonstrates an upward trend from 2019 to 2020, with a 17.8% increase. However, it subsequently declines from 2020 to 2022, with a decrease of 0.7% from 2020 to 2021 and a further decrease of 8.7% from 2021 to 2022. The decomposition of the total factor productivity index reveals that the main reason for the decline in the index between 2020 and 2021 is the decrease in the technical progress index, while the decline between 2021 and 2022 is attributed to the decrease in the technical efficiency index. Further analysis shows that the decline in the technical efficiency index can be traced back to both the PECH index and the SECH index. It becomes evident upon closer examination that the decrease in the technical efficiency index is linked to the simultaneous decrease in both the PECH index and the SECH index.

Out of all the enterprises, 14 of them, accounting for 58.3% of the total, have shown a growth trend in their total factor productivity index between 2019 and 2022. Seven of these enterprises have experienced a growth rate of more than 10%, with A23 exhibiting the largest growth rate at 37.1% over the 4-year period. However, 10 out of the 24 enterprises have demonstrated a decreasing trend in their total factor productivity index: A21, A17, A2, A13, A4, A19, A15, A18, A22, and A6, respectively. An analysis of the reasons for the declining trend in these 10 enterprises, conducted by decomposing the total factor productivity, indicates that the technical efficiency change index of these enterprises is lower than 1, reflecting a declining trend. This suggests that the primary factor contributing to the decrease in the total factor productivity index of these 10 enterprises is the decline in their technical efficiency. Specifically, the technical efficiency change index and the technical progress index of A2 are both lower than 1, and the decline in the total factor productivity index of A2 can be attributed to the simultaneous decline in the technical efficiency change index and the technical progress index. Further decomposition of the technical efficiency change index reveals that the PECH change index and scale efficiency change index of enterprises A21, A2, A4, A15, and A65 demonstrate a declining trend. This indicates that the technical efficiency change index of these five businesses has decreased due to an inadequate resource allocation capacity and an unreasonable scope of operations. On the other hand, the SECH change index of enterprises A17, A19, A18, A13, and A22 is attributed to the decline in the total factor productivity index caused by the decrease in the PECH change index. Based on the above conclusions, enterprises A13 and A22 should prioritize improving their resource allocation capacity and management level to prevent a further decline in the PECH index and effectively enhance their total factor productivity index. Enterprises A17, A19, and A18, on the other hand, need to focus on adjusting their development scale and improving their SECH to prevent a further decline in the SECH index and maintain their output efficiency. Additionally, enterprises A21, A2, A4, A15, and A6 should consider adjusting their resource allocation capacity, management level, and development scale. It is crucial for these enterprises to recognize the interplay between R&D inputs and outputs and strengthen their technological capabilities and the efficiency of technological transformation.

In the aforementioned study, although the overall total factor productivity showed an upward trend, the effectiveness of green technology innovation was impeded by an insufficient technical efficiency within the firms and a low input–output ratio. Consequently, water environment governance enterprises should prioritize the rationality of their research and development investment, optimize the input–output ratio, and establish clear targets and expected conversion rates for technological transformation [20].

## 4. Conclusions

In this paper, we analyzed the GTIE of 24 listed Chinese water treatment companies by selecting micro enterprise data from 2019 to 2022 and processed the relevant indicator data. We then applied the Malmquist DEA model to quantitatively analyze the factors that influence these companies and constructed a theoretical framework to further investigate their influencing mechanisms.

Our research findings indicate that the average PECH of these 24 companies during the aforementioned period is 0.912; the average value of EFFCH is 0.88; the average SECH is 0.964; and the average TFPCH is 1.022. While the average values are relatively high and the TFPCH increased by 2.2% during the studied period, most companies' indices do not exceed the average.

Currently, China's water environment treatment enterprises are experiencing an overall upward trend in their GTIE. However, there is still significant room for improvement, particularly in terms of their ability to translate R&D inputs into technological innovation outputs. Specifically, these enterprises demonstrate a commendable level of PECH and SECH. However, there is a noticeable disparity in efficiency among them, and a strong positive correlation exists between PECH, SECH, and EFFCH. This suggests that technological progress and the development scale are the primary factors influencing EFFCH. Furthermore, their total factor productivity is generally increasing, but it has shown a tendency similar to an "inverted U" over the past four years. There is a considerable variation in the total factor productivity across enterprises, with those performing better in this aspect typically exhibiting higher levels of innovation. Additionally, in the analysis of the causes of innovation efficiency, R&D inputs, the resource allocation capacity, and the management level have been found to have a significant impact on EFFCH. Increasing R&D inputs can lead to higher outputs in green technology innovation, indicating a growing market demand for such innovations. However, the existing input and output levels of these enterprises often fall short of meeting the market demand. This suggests that while increasing R&D inputs can boost technological innovation outputs proportionally, blindly increasing these inputs may lead to a decline in GTIE. Moreover, a low resource allocation capacity and an excessive development magnitude have a detrimental effect on the innovation indices.

This study offers the following recommendations: Firstly, in terms of internal enterprise management, there should be a focus on prioritizing the training and recruitment of skilled individuals in the field of water governance. This will involve establishing a team with professional skills and expertise, enhancing the professionalism of employees, and providing robust talent support to drive the transformation and development of enterprises. Additionally, companies should actively cultivate collaborative partnerships with the government, universities, scientific research institutions, and other entities to collectively advance the development and implementation of water treatment technologies. Through industry–academia–research cooperation, there can be resource sharing, complementary strengths, and the promotion of technological innovation and the transformation of achievements. Secondly, enterprises need to improve their awareness of technological innovation and enhance the effectiveness of water environment management. To achieve dynamic efficiency, organizations should develop a dynamic intelligent decision support system that utilizes artificial intelligence's self-learning and optimization capabilities to identify and rectify product operational deficiencies, thereby improving and optimizing their products. Continuous data collection, feedback analysis, and strategy adjustments can enhance the efficiency of water environment management. Furthermore, although the aforementioned study did not research and analyze government policies and subsidies, it is clear that the water environment treatment industry has significant policy-oriented characteristics, and its development status and prospects are closely linked to the government's macro-policy orientation and measures. The government should facilitate the transformation of sewage treatment enterprises into water governance enterprises using financial subsidies, tax incentives, and other policy measures, reducing the enterprises' transformation expenses and increasing their enthusiasm. Additionally, the government should increase financial investment into the field of water treatment and provide financial support for original and breakthrough technological innovations and project implementation on the part of enterprises [21]. By setting up special funds and guiding social capital investment, the government can promote the development and application of water governance technologies. At the same time, the government should focus on improving the regulatory mechanisms and strengthen the supervision and assessment of water governance enterprises by formulating relevant regulations and standards to ensure that the capital operation norms and technical levels of water governance enterprises meet the required standards.

## 5. Contribution and Limitations

When it comes to researching green technology innovation and its efficiency, the current emphasis lies predominantly on provincial or macro-level studies of industries, manufacturing, and new technology sectors. These studies extensively rely on yearbook data and industry-specific information, resulting in limited utilization of company annual report data. As a result, a precise and thorough understanding of green innovation at the company level remains lacking. This article aims to address this research gap by examining green technology innovation and evaluating its efficiency specifically in water environment management companies. By utilizing annual report data, this study adopts a micro perspective and analyzes technical efficiency, scale efficiency, and total factor productivity from both static and dynamic viewpoints. By offering specific and comprehensive research, this study contributes to the academic community and holds practical implications for promoting green development within the water management industry and its enterprises.

Regarding the measurement methods, this study employs the Malmquist DEA approach to analyze the time span and further enhances the use of the DEA model. The findings of this study offer valuable insights for Chinese water treatment companies with respect to research and development (R&D) technology and expansion strategies. They assist companies in adapting production factors based on the research conclusions, thereby improving the efficiency of corporate green technology innovation, advancing water environment management, and utilizing technology to enhance the effectiveness and standards of ecological restoration.

This article still has certain limitations in terms of the data selection and processing. Due to time constraints and the nature of panel data indicators, this paper is unable to provide a more extensive analysis and response to the changes in green technology innovation among water environment management organizations. Given the evolving socio-economic and political landscape in China and globally, the ecological environment and natural resources will face a more diverse and complex scenario. In our future research, we intend to further investigate the performance of the listed firms in our country that are involved in green technology innovation for water environment management. We also plan to expand the scope of our study to include the examination of green development in other emerging economies. Additionally, we aim to employ diverse research methodologies to explore efficiency from different perspectives, with the goal of understanding the current state of water environment governance among the listed companies in our country and assessing their effectiveness. This comprehensive investigation into the establishment and operation of water environment management enterprises is crucial. Further study in this field is essential for advancing water and environmental management businesses. It will help us gain a better understanding of the factors influencing the effectiveness of innovation in water governance companies and enable us to develop strategies for enhancing this efficiency. This knowledge is valuable for the government, academia, and the business community.

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