Scientific Research Publishing

Journal of Service Science and Management, 2025, 18(6), 541-573
https://www.scirp.org/journal/jssm
ISSN Online: 1940-9907
ISSN Print: 1940-9893

Evaluating the Impact of "Smart Water" on the Management and Technical Efficiency of Water Supply Utilities: Evidence from Investigation on Shandong Province in China

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How to cite this paper: Liu, X. F., Ma, Z. Y., & Li, H. Y. (2025). Evaluating the Impact of "Smart Water" on the Management and Technical Efficiency of Water Supply Utilities: Evidence from Investigation on Shandong Province in China. *Journal of Service Science and Management, 18,* 541-573.
https://doi.org/10.4236/jssm.2025.186033

Received: September 10, 2025
Accepted: December 22, 2025
Published: December 25, 2025

Abstract

The healthy development of the water supply industry is directly correlated with the quality of urban development. Utilizing survey data from water supply utilities in Shandong Province between 2010 and 2016, this study employs KLH model to assess both management efficiency and technical efficiency. The findings reveal that: 1) Technical and management efficiencies for Shandong's water supply utilities are 70.6% and 72%, respectively, resulting in a compound efficiency of 52.9%. 2) Implementing "Smart Water" infrastructure in Shandong Province enhances technical and management efficiencies by approximately 11.7% and 11.5%, respectively, leading to a centralized trend in these aspects for water supply utilities within the province. 3) The mediating effect of "Smart Water" infrastructure on technical outcomes primarily manifests through enterprise scale, while its influence on management outcomes mainly stems from optimizing high-tech talent structures. Consequently, this paper proposes policy recommendations and strengthening support in planning, standards, technology and talent.

Keywords

Technical Efficiency, Management Efficiency, KLH Model, "Smart Water", Water Supply Utilities

1. Introduction

As high-quality urban development continues to advance in China, the importance of the water supply industry is becoming more pronounced due to its crucial role in sustaining urban ecological environments and driving economic growth[1]. In order to improve management and technical efficiency within this sector, continuous optimization efforts have been undertaken by both the Central Committee of the Communist Party of China and relevant ministries through a series of policy reforms aimed at enhancing performance. In January 2015, the National Development and Reform Commission, in collaboration with the Ministry of Housing and Urban-Rural Development, released "Guiding Opinions on Accelerating the Establishment of an Optimal Urban Residential Water Tiered Pricing System," which comprehensively outlined implementation details for a tiered water pricing system among urban residents while enhancing pricing mechanisms within the water supply industry. In February 2014, ten ministries including the Ministry of Water Resources and National Development and Reform Commission issued an "Implementation Plan for Rigorous Assessment Work on Water Resources Management System" to improve efficiency in urban water supply through enhanced accountability systems, water pricing mechanisms, as well as management frameworks.

The "Fourteenth Five-Year Plan for National Economic and Social Development and the Long-Range Objectives Through the Year 2035" of the People's Republic of China consistently emphasizes key themes such as "establishing intelligent cities and digitalizing rural areas", "comprehensively enhancing urban quality", and "strengthening water infrastructure construction". This indicates that, on one hand, the future focus of urban development and management will be on prioritizing the water supply industry. On the other hand, there is a gradual transition towards refined and intelligent management in this sector. However, an unresolved issue currently revolves around evaluating the efficiency of both management and technical aspects within China's water supply utilities. To what extent does local implementation of "Smart Water" impact these utilities' efficiency? These questions remain largely unanswered, particularly concerning the calculation of management efficiency. From a practical perspective, inadequate evaluation of both management and technical efficiency within water supply utilities will undoubtedly hinder investment levels and impede further development amidst increasing government oversight and improved policies/regulations in Chinese cities.

Therefore, the effective measurement and evaluation of management efficiency and technical efficiency in water supply utilities, as well as the analysis of the role played by "Smart Water" infrastructure development, constitute the fundamental research objectives of this study. Thus, this paper aims to adopt Kumbhakar et al.'s (2012) research methodology and construct the KLH model. Micro-level data from water supply utilities in Shandong Province between 2010 and 2016 are employed to separately estimate their management efficiency and technical effi-

[1]Wang Yuanyuan. "Business Model, Competitive Landscape, Entry Barriers, and Development Trends in the Water Industry" is sourced from "China Economic Intelligence Network". Website: https://www.h2o-china.com/news/310172.html

ciency. Additionally, this paper aims to assess and investigate the mechanisms by which the implementation of "Smart Water" in Shandong Province generates effects and policy impacts, thereby providing constructive suggestions for optimizing the water supply industry. The potential innovations of this study can be summarized as follows: Firstly, it utilizes specific characteristics pertaining to management efficiency within water supply utilities in Shandong Province that encompass information on individual effects; these levels of management efficiency and technical efficiency are subsequently calculated using the constructed KLH model. Secondly, it comprehensively evaluates the marginal effects of implementing "Smart Water" in Shandong Province on urban water supply industry efficiency based on calculations while exploring its underlying mechanisms; thus offering valuable recommendations for future government policy optimization.

The rest of this article is organized as follows: The second part provides a comprehensive literature review, focusing on the implementation of "Smart Water" and its supporting construction system. The third part constructs an efficiency calculation model (KLH model) for the urban water supply industry and elaborates on the strategy for efficiency identification and calculation. In the fourth part, we describe the data source, variable selection, and variable processing methods used in this study. The fifth part constitutes the core section of this paper where we estimate management and technical efficiency of water supply utilities using estimation strategies and identification methods with Shandong Province's water supply utilities as an example. The sixth part analyzes in depth the influence and impact of "Smart Water" construction on the water supply industry, particularly examining its role in technical and management efficiency improvement. Finally, in the seventh part, we summarize our findings from this study and provide targeted policy suggestions.

2. Literature Review and Implementation Strategy of "Smart Water" Construction in Shandong

2.1. Literature Review

When measuring the development and technological level of the water supply industry, scholars have traditionally relied on single indicators to describe and characterize it. For instance, per capita urban water supply volume (Mansur and Olmstead, 2012), enterprise operating income (Cabrera, 2008), and urban water supply capacity (Cabrera, 2008) have been used to gauge the level of water affairs development and performance in this sector (Li, 2018). While these measurement methods offer intuitive advantages, their singularity and endogeneity issues have led to a shift towards systematic approaches for calculating industry technical efficiency. In terms of measuring the technical efficiency level of utilities or industries, two commonly adopted methods in academia are parameter estimation and non-parameter estimation (Jun-Yen, 2005). Stochastic Frontier Analysis (SFA) is widely recognized as a reliable parameter estimation method, whereas Data Envelopment Analysis (DEA) is predominantly employed as a non-parameter estimation method (Benito et al., 2019). Both analysis techniques possess distinct advantages; SFA leverages economic theory through stochastic frontier modeling to yield results that align closely with theoretical assumptions (Hossin et al., 2023), while DEA estimates optimal frontier surfaces directly based on data characteristics without any predefined models, thus avoiding artificial intervention concerns (Charnes et al., 1978). However, from the perspective of measuring the efficiency of water supply industry and economic analysis, scholars tend to favor using the stochastic frontier analysis method (Daraio et al., 2020; Worthington, 2014).

On the one hand, due to the water supply industry's classification as a public utility field, numerous classical economic models have been established in this domain (Lin, 2005), such as the vertical integration model of water supply (Saal et al., 2013; Carvalho & Marques, 2014) and the government regulation model of water supply utilities (Thanassoulis, 2000; Camanho et al., 2022; Cetrulo et al., 2019). On the other hand, compared to data envelopment analysis (DEA), the stochastic frontier analysis method has demonstrated innovation and continuous improvement with approaches like Meta-SFA (Meta-Stochastic Frontier Analysis) (Lin, 2005; Battese et al., 2004; O'Donnell et al., 2008) and Latent-Class-SFA (Latent-Class Stochastic Frontier Analysis) (Orea & Kumbhakar, 2004; Greene, 2005a). Concerning research on utilizing the stochastic frontier analysis method for calculating technical efficiency and management efficiency of utilities, Pitt and Lee (1981) were pioneers in proposing its application through employing random effects models to calculate individual effects within panel data. They posited that the concentration of management efficiency often manifests in individual effects due to the limited ability of utilities to make significant short-term adjustments. However, given the constraints of econometric techniques at that time, Pitt and Lee (1981) assumed that the individual effect and error terms of the model followed absolute standard normal distribution and standard normal distribution, respectively. Subsequently, scholars such as Kumbhakar (1990), Battese and Coelli (1988), Cuesta (2000), and Greene (2005a) (see also Greene, 2005b) continuously refined the model by considering various assumptions regarding the composition of individual fixed effects, thereby enhancing the accuracy of management and technical efficiency estimation. Eventually, Kumbhakar, Lien, and Hardaker (2012) proposed a comprehensive "normal-semi-normal" stochastic frontier model (referred to as KLH model) for disentangling and identifying enterprise-level management efficiency from technical efficiency. Tsionas and Kumbhakar (2014) summarized this KLH model while introducing a theoretical framework based on truncated normal distribution assumption along with maximum likelihood estimation technique (MLE) for identifying both technical efficiency and management efficiency.

The research on efficiency measurement of water supply utilities or industries primarily focuses on the calculation of factor productivity. Bosworth and Stoneman (1998) utilized data from European water companies spanning from 1979 to

1995, revealing a labor factor productivity change of 2.2% between 1979 and 1989, followed by a mere increase of 0.03% between 1989 and 1995, without considering the capital factor. Saal and Parker (2001) computed the water companies in England and Wales during the period from 1985 to 1999, indicating an approximate total factor productivity change of around 2.3% between 1985 and 1990, followed by a decrease to approximately 2.1% between 1990 and 1995, and 1% between 1995 and 1999. Woodbury and Dollery (2004) used data from the Australian Consultative Committee report from 1999 to 2000 and found that the average technical efficiency was about 73.7%, and the scale efficiency was approximately 79.8%. Lin (2005) calculated using data from China from 2002 to 2012 and found that the average technical efficiency in China ranged from 45% to 89%. Minzhe Du et al. (2023) showed that the U-shaped trend in cost technology gap ratio appeared in the urban water supply industry in China during the period from 2001 to 2016, and the production technology of cities with moderate water shortage is closest to the optimal production frontier.

In summary, our findings indicate that the academic community primarily focuses on measuring the technical efficiency and factor productivity of water supply utilities. However, there remains a gap in separating and calculating the stochastic frontier model-based technical efficiency and management efficiency of these utilities. This limitation hinders effective identification of the true source of efficiency in water supply analysis, making it challenging to provide targeted recommendations and strategies. Therefore, this paper aims to introduce Kumbhakar et al. (2012)'s research approach into the field of efficiency measurement in the water supply industry. By leveraging the characteristic slow adjustment of management efficiency in the short term, we can extract relevant management information from individual enterprise effects to calculate their management efficiency, thus achieving separation between management and technical efficiencies. Additionally, this paper also analyzes the impacts and mechanisms of external factors such as "Smart Water" based on measurements of technical and management efficiencies. This fills a crucial gap in efficiency measurement within the water supply industry while providing a foundation for government policy formulation.

2.2. Process of "Smart Water" in Shandong

The smart water system primarily utilizes advanced information technology to automate the monitoring of water quality, replacing manual methods through data mining and scene application matching. This enables efficient operations, scientific management, and timely emergency response in water utilities. Consequently, the key advantages of smart water in water management are as follows: firstly, it ensures the safety of urban water supply and plays a crucial role in fostering social stability and constructing a harmonious society; secondly, it significantly enhances the quality of urban water supply, thereby improving people's quality of life and promoting comprehensive urban economic development; thirdly, it greatly improves the provision of water services. Under the influence of a smart water system, not only should the water supply unit produce aquatic products that meet standards but also enhance their own safety measures for supplying clean drinking water while increasing service awareness. This ensures that the provision of safe drinking water becomes more intelligent, user-friendly, and modern without compromising on its quality or safety.

The "12th Five-Year Plan" of China proposes the utilization of "Smart Water" to facilitate the integration of informatization and industrialization in the water supply industry. In 2010, municipal water supply utilities in Shandong Province initiated the construction of "Smart Water" infrastructure. In 2011, to further implement the national development plan, Shandong Province officially incorporated "Smart Water "into the framework of its "Smart City" system, thereby promoting urban management modernization across Shandong Province. In 2012, Shandong Province officially launched the pilot work of smart city construction. The former Shandong Economic and Information Commission issued *the Notice on Carrying Out the Pilot Work of Smart City Construction*; among seven major pilot areas identified by former Shandong Provincial Economic and Information Commission was one called "Smart Water", which aimed at clarifying hydrological resource construction and integration with facilities such as those for drainage and sluice stations while strengthening information sharing with other departments responsible for city appearance greening, transportation construction, local maritime activities etc., carrying out comprehensive business applications including monitoring and forecasting as well as prior warning systems during process evaluation stages before post-evaluation is conducted so that intelligent command over water security can be achieved along with scheduling resources intelligently while also monitoring environmental factors related to groundwater quality or rainfall levels through planning an "intelligent" sensing network system.

In recent years, the Shandong Provincial Government has formulated the Digital Shandong Development Plan (2019-2022). Simultaneously, a series of documents including the "Shandong Province Digital Government Construction Implementation Plan (2019-2022)", "Opinions on Supporting the Development of Digital Economy in Shandong Province", and "Work Plan for Pilot Demonstration Construction of New Smart Cities in Shandong Province" have been issued by the Digital Shandong Construction Special Group Office. Among these documents, the pilot construction of new smart cities is being carried out in three batches at provincial level, with approximately 10 cities and 30 counties (cities/districts) participating to create exemplary models. Water quality monitoring plays a crucial role in smart city construction. These policies and measures establish an institutional framework for smart water utilities development in Shandong Province and provide significant policy support for advancing smart water initiatives. Furthermore, the Urban Water Supply Standardization Appraisal System has been established by the Live Built Hall of Shandong Province to ensure security monitoring systems are implemented along with network operation data collection and automatic scheduling systems that can effectively collect information on water quality, pressure, and flow into an assessment index system. This promotes enhanced levels of wisdom-based management within water supply utilities.

In 2019, a comprehensive field survey was conducted in Shandong Province to assess the information system construction of water supply utilities within its jurisdiction. The survey encompassed the provincial cities, including districts and county-level counties, involving a total of 16 cities with districts, 11 county-level cities, and 15 counties (districts), thereby covering 50 water supply utilities. The primary focus of this field survey comprised evaluating the existing information systems of these utilities, examining their planned system constructions as well as assessing the prevailing hardware infrastructure. Based on the findings obtained from this survey, it was revealed that among the aforementioned 50 water supply utilities across these 16 cities, a total of 225 information systems have been established to cater to various aspects such as command dispatch, production and operation, business charges, SCADA system along with DMA system. These systems accounted for approximately: command and dispatch (16%), production and operation (19%), business charges (20%), SCADA system (17%), DMA system (2%) respectively; further details can be found in **Figure 1**.

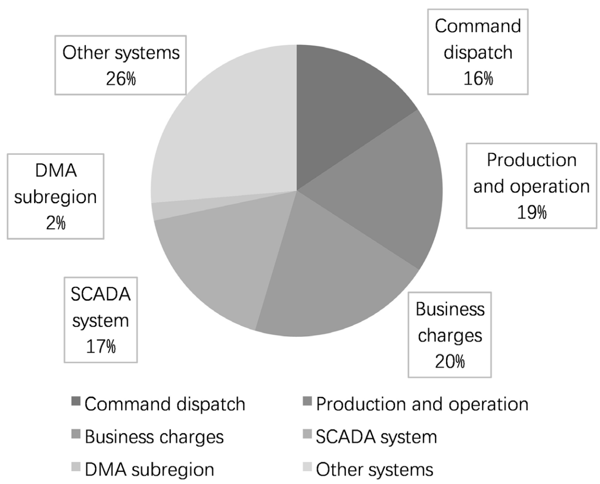

Figure 1. Information system of water supply utilities in Shandong Province.

According to the existing research data analysis, cities in Shandong Province in recent years have made great achievements in informatization, the construction of production, revenue, network scheduling management and service and other business areas of professional information system, which fits for adapting to the requirements of high-quality development and improving the management quality and level. From the quantity of information system construction, urban information system construction is relatively comprehensive, the content of urban information system construction is relatively single, and the number is significantly less than that of urban water supply utilities; In addition, the information construction in the eastern coastal areas of Shandong is relatively fast, and the information system construction in the western inland areas is relatively backward, showing significant regional differences. In addition, according to the information of the Shandong Provincial government website, there are 16 cities and 136 county-level districts (58 municipal districts, 26 county-level cities and 52 counties). The penetration rate of information system is not high, and the degree of information management is relatively low (Table 1).

Table 1. Number of water supply utilities in districts and cities within Shandong Province as of 2019.

City	Command dispatch	Production and operation	Business charges	SCADA system	DMA subregion	Other systems	Amount
Jinan	1	4	4	2	1	2	14
Qingdao	1	2	1	1	0	0	5
Zibo	5	4	6	11	0	10	36
Zaozhuang	0	0	1	1	0	1	3
Dongying	3	4	4	4	1	8	24
Yantai	3	0	4	3	2	4	16
Weifang	2	7	3	4	0	15	31
Jining	2	5	2	2	0	9	20
Taian	4	3	5	4	0	6	22
Weihai	1	1	1	0	0	3	6
sunshine	2	1	2	2	0	0	7
Linyi	3	1	2	2	0	2	10
Liaocheng	1	1	2	1	0	0	5
Texas	0	2	2	2	1	4	11
Binzhou	2	1	2	1	0	0	6
Heze	2	2	2	2	0	1	9
amount to	32	38	43	42	5	65	225

Notes: The author made statistics and sorted out the actual investigation.

Currently, there exist significant disparities in the stage of smart water utilities construction in Shandong Province. Overall, the information data construction and modular operation stages of certain business systems have been essentially completed. Jinan and Qingdao are currently engaged in the planning and construction phase of a data fusion and integrated information scheduling platform. The development of smart water utilities entails digitizing enterprise resources, management, technology, and services for water supply utilities. This involves reconstructing the management process to align with the requirements of information management laws while incorporating process optimization measures. By gathering information on enterprise resources, management, technology, and services through big data analysis, Internet of Things integration, cloud computing utilization among other means; an in-depth analysis can be conducted on production operations and utility management that were previously unattainable using traditional methods. Consequently, valuable insights facilitating decision-making or enhancing efficiency can be derived from this analysis-driven approach underpinned by the "wisdom" wave driving innovative changes to water utility management modes resulting in significantly improved operational efficiency for these entities. Particularly within Shandong Province's comprehensive promotion strategy for "Smart City", current smart water supply primarily manifests itself within office settings as well as communication and production domains; however, there remain some deficiencies regarding early warning system establishment and emergency response mechanisms.

3. Econometric Model and Estimation Strategies

3.1. Research Hypotheses and the Design of Econometric Model[2]

Drawing on the research approach of Kumbhakar, Lien, and Hardaker (2012) (referred to as the KLH model), this study sets the stochastic frontier econometric model as follows:

$$\ln y_{it} = \alpha_0 + \ln f_{it}^{*}\left(x_{it}, \beta\right) + \ln X_{it} + \alpha_i - \eta_i - v_{it} + \varepsilon_{it} \quad (1)$$

In Equation (1), $\ln f_{it}^{*}\left(x_{it}, \beta\right)$ represents the optimal production function, which is assumed to be in the form of a Cobb-Douglas function in this study. x_{it} represents the set of corresponding input factors for water supply utilities, including labor, fixed asset investment, chemical input, energy input, and other aspects. β represents the vector of elasticity coefficients for input factors. X_{it} represents the vector of control variables for the characteristics of water supply utilities in Shandong Province. In Equation (1), v_{it} represents the technical inefficiency, while η_i represents the management inefficiency of individual entities. τ_i is assumed to be the individual random effects of water supply utilities, following the true individual effects model proposed by Greene (2003) (see also Greene, 2005b; Greene, 2005c), and α_i is therefore considered as a random disturbance term with a distribution, $N\left(0, \sigma_\alpha^2\right)$. α_0 represents the constant term, while ε_{it} represents the random disturbance term of the model. We can combine and rearrange Equation (1) as follows:

$$\ln y_{it} = \alpha_0^{*} + \ln f_{it}^{*}\left(x_{it}, \beta\right) + \ln X_{it} + \tau_i + \epsilon_{it} \quad (2)$$

In Equation (2), $\alpha_0^{*} = \alpha_0 - E\left(\eta_i\right) - E\left(v_{it}\right)$, $\tau_i = \alpha_i - \eta_i + E\left(\eta_i\right)$, $\epsilon_{it} = \varepsilon_{it} - v_{it} + E\left(v_{it}\right)$. We can see that ϵ_{it} in Equation (2) is a composite perturbation term, which does not satisfy the classical assumption of white noise in ordinary least squares (OLS). However, since we assume that ε_{it} is a disturbance term obeying $N\left(0, \sigma_\varepsilon^2\right)$ distribution, v_{it} obeys $N^{+}\left(Ev, \sigma_v^2\right)$ semi-normal distribution, ϵ_{it} also follows a normal distribution with a mean of Ev and a constant variance. Therefore, when estimating the parameters of the optimal production function, this paper primarily utilizes the Generalized Least Squares (GLS) method for unbiased estimation.

[2]This study utilizes self-programmed calculations and statistics using Stata 15.0 software. Readers who require the corresponding commands can request them from the author.

3.2. Estimation and Measurement Strategy

Building upon the measurement of management and technical efficiency models discussed earlier, this paper divides the corresponding estimation strategy into the following five steps.

Step 1: Since ϵ_{it} follows a normal distribution with a mean of 0 and a constant variance, the GLS estimation is applied to Equation (2) to obtain consistent estimates of the parameters in the individual random effects model, denoted as $\hat{\beta}$. Simultaneously, we can estimate the values of individual random effects and parameter terms, denoted as $\widehat{\tau_i}$ and $\widehat{\alpha_0^*}$, respectively.

Step 2: For individual water supply utilities, management efficiency information is generally reflected in individual-level data. Therefore, we attempt to separate the management efficiency from the individual effects of the enterprise (Pitt & Lee, 1981), setting the management inefficiency term as η_i, resulting in Equation (3). Under the assumption of $\alpha_i \sim N\left(0, \sigma_\alpha^2\right)$ and conditional on $\eta_i \sim N^+\left(\mu_i, \sigma_{\eta,i}^2\right)$, we employ the estimation method proposed by Battese and Coelli (1988), using the estimated value of $\widehat{\tau_i}$ obtained in the first step and the expression of Equation (3) to conduct stochastic frontier estimation.

$$\tau_i = \alpha_i - \eta_i + E\left(\eta_i\right) \tag{3}$$

In this equation, $\mu_i = z_i'\delta$ and $\delta_{\eta,i}^2 = \exp\left(z_i'w\right)$. To further investigate the impact of implementing "Smart Water" on the management efficiency of water supply utilities, this study sets z_i as a dummy variable representing the implementation of "Smart Water". Specifically, $z_i = 1$ indicates that the water supply enterprise has implemented smart water management, while $z_i = 0$ indicates the absence of smart water management. On the other hand, δ and w represent the corresponding coefficients and weight coefficients, respectively. Therefore, this study obtains the actual management efficiency value $\text{Man}_{\text{efficiency}}$ of urban water supply utilities, which is represented as $\text{Man}_{\text{efficiency}} = \exp\left(-\eta_i \mid \epsilon_{it}\right)$.

$$\text{Man}_{\text{efficiency}} = \exp\left(-\eta_i \mid \alpha_i\right) = \exp\left(-\mu_{\eta^*} + \frac{1}{2}\sigma_{\eta^*}^2\right) \frac{\Phi\left(\frac{\mu_{\eta^*}}{\sigma_{\eta^*}} - \sigma_{\eta^*}\right)}{\Phi\left(\frac{\mu_{\eta^*}}{\sigma_{\eta^*}}\right)} \tag{4}$$

In Equation (4), μ_{η^*} and $\sigma_{\eta^*}^2$ are respectively represented as $\frac{\mu_i \sigma_{\eta,i}^2 - \alpha\sigma_\alpha^2}{\sigma_{\eta,i}^2 + \sigma_\alpha^2}$ and $\frac{\sigma_{\eta,i}^2 \sigma_\alpha^2}{\sigma_{\eta,i}^2 + \sigma_\alpha^2}$.

Step 3: For the technical efficiency of utilities, it generally adjusts and changes in a timely manner with the operation of the enterprise. Therefore, technical efficiency often varies both over time and across individuals, with its inefficiency term denoted as v_{it}. In the first step, we can obtain the estimated value of the residual term, denoted as $\widehat{\epsilon_{it}}$. Additionally, we employ the estimation method proposed by Battese and Coelli (1988). Under the assumption that ε_{it} obeys

$N\left(0,\sigma_{\varepsilon}^{2}\right)$ and v_{it} follows a truncated normal $N^{+}\left(0,\sigma_{v}^{2}\right)$ distribution, we use the results obtained in the first step to conduct maximum likelihood estimation on Equation (4).

$$\epsilon_{it} = \varepsilon_{it} - v_{it} + E\left(v_{it}\right) \tag{5}$$

In this equation, $\delta_{v}^{2} = z_{it}'\theta$, z_{it} represents the implementation of "Smart Water" measures in water supply utilities, and θ represents the corresponding coefficient. Based on the aforementioned estimation strategy, this study obtains the technical management efficiency value of water supply utilities, $\mathrm{Tech}_{\mathrm{efficiency}}$, which is denoted as $\mathrm{Tech}_{\mathrm{efficiency}} = \exp\left(-v_{it} \mid \epsilon_{it}\right)$.

$$\mathrm{Tech}_{\mathrm{efficiency}} = \exp\left(-v_{it} \mid \varepsilon_{it}\right) = \exp\left(-\mu_{v*} + \frac{1}{2}\sigma_{v*}^{2}\right)\frac{\Phi\left(\frac{\mu_{v*}}{\sigma_{v*}} - \sigma_{v*}\right)}{\Phi\left(\frac{\mu_{v*}}{\sigma_{v*}}\right)} \tag{6}$$

In Equation (6), μ_{v*} and σ_{v*}^{2} are respectively represented as $\frac{-\varepsilon\sigma_{\varepsilon}^{2}}{\sigma_{v}^{2}+\sigma_{\varepsilon}^{2}}$ and $\frac{\sigma_{v}^{2}\sigma_{\varepsilon}^{2}}{\sigma_{v}^{2}+\sigma_{\varepsilon}^{2}}$.

Step 4: Building upon the second and third steps, this paper can obtain the comprehensive efficiency level of water supply utilities in Shandong, which is represented by Equation (7):

$$\begin{aligned}\mathrm{Overall}_{\mathrm{efficiency}} &= \exp\left(\text{Total efficiency loss} \mid \epsilon_{it}\right) = \exp\left(-v_{it} - \eta_{i} \mid \epsilon_{it}\right) \\ &= \exp\left(-v_{it} \mid \epsilon_{it}\right) * \exp\left(-\eta_{i} \mid \epsilon_{it}\right) = \mathrm{Tech}_{\mathrm{efficiency}} * \mathrm{Man}_{\mathrm{efficiency}}\end{aligned} \tag{7}$$

Step 5: Calculate the marginal effects of implementing "Smart Water" construction in Shandong's water supply utilities. In order to further analyze the impact of implementing "Smart Water" on enterprise efficiency in Shandong, this paper adopts the marginal effects model construction method proposed by Wang and Schmidt (2002). The formula for the marginal effects of "Smart Water" construction is obtained as follows:

$$\begin{aligned}\frac{\partial E(I)}{\partial z} &= \beta_{1}[z]\left\{1 - \Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right] - \left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^{2}\right\} \\ &\quad + \beta_{2}[z]\frac{\sigma_{I}}{2}\left\{\left(1+\Delta^{2}\right)\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right] + \Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^{2}\right\}\end{aligned} \tag{8}$$

And

$$\begin{aligned}\frac{\partial D(I)}{\partial z} &= \frac{\beta_{1}[z]}{\sigma_{I}}\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]\left[E(I)^{2} - D(I)\right] \\ &\quad + \beta_{2}[z]\sigma_{I}^{2}\left\{1 - \frac{1}{2}\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]\left\{\Delta + \Delta^{3} + \left(2+3\Delta^{2}\right)\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right] + 2\Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^{2}\right\}\right\}\end{aligned} \tag{9}$$

In Equations (8) and (9), I is represented as either v_{it} or η_{i}, and z represents the policy variable of implementing "Smart Water" construction. Additionally, $\beta_1[z]$ and $\beta_2[z]$ in the equation represent the weight coefficients of the respective policy variables, while Δ represents $\frac{I}{\sigma_I}$. Therefore, this study can determine the impact of policy variables on efficiency losses. Specifically, Equations (8) and (9) respectively represent the influence of "Smart Water" measures on the mean and volatility of the inefficiency component.

4. Data and Variables

4.1. Data Source and Description

The data utilized in this study primarily originates from the operational records of water supply utilities across various cities in Shandong Province over an extended period. This comprehensive database was collaboratively established through field investigations conducted by the authors and the Shandong Provincial Urban Water Supply and Drainage Water Quality Monitoring Center. It encompasses 45 water supply utilities located within 16 prefecture-level cities in Shandong Province, encompassing their operational aspects, water supply dynamics, and water quality conditions. The temporal scope spans from 2010 to 2016[3]. To ensure privacy protection for individual utility entities, a de-identification process has been applied to the database. Notably, it should be acknowledged that during the survey and subsequent data processing stages, significant changes occurred in terms of the number of water supply utilities within the Shandong region due to factors such as alterations, new constructions, mergers, and reorganizations. The survey methodology employed herein is primarily based on categorizing utilities according to whether they maintain independent financial accounting practices or not; if a group company adopts unified accounting procedures, it is treated as a single enterprise within this study's framework.

4.2. Variables

The variable selection in this paper primarily relies on the identification and estimation strategies, as well as econometric models discussed earlier. Specifically, the Cobb-Douglas form is employed to estimate the production function, incorporating total electricity consumption, net value of fixed assets, total consumption of chemicals, and the number of employees as input variables. To account for water supply product quality, this study integrates an assessment of reasonable tap water quality into the analysis, making high-quality water supply the main output variable. Consequently, variable selection in this paper is predominantly guided by identification and estimation strategies and encompasses input-output indicators within the production model section (Model 2), along with exogenous shock variables within efficiency estimation models (Models 8 and 9).

[3]The actual survey data also includes data from 2017 and 2018, due to the significant absence of key indicators, this article did not utilize them.

4.2.1. Production Model Part

The main output of this paper is the high-quality water supply volume of water supply utilities in Shandong Province, referred to as Lny_b. This indicator is mainly derived from the processing of the total water supply volume of the enterprise and the comprehensive water quality rationality rate index. Its formula is as follows:

$$\text{Lny\_b} = \text{Lny} \cdot \text{Rate}$$

In this context, Lny represents the actual water supply volume of water supply utilities in Shandong Province, while Rate represents the comprehensive water quality compliance rate. This compliance rate is mainly based on the monitoring results of the national "Hygienic Standard for Drinking Water". It includes compliance rates for turbidity, color, odor and taste, residual disinfectant concentration, total colony count, total coliform count, and chemical oxygen demand (CODMn). This paper presents the average levels of total water supply and high-quality water supply, as shown in Figure 2. It can be visually observed that although there was a brief decline from 2012 to 2013, the overall trend from 2010 to 2016 shows a gradual improvement in the level of high-quality water supply. This clearly indicates that the rapid urban development has led to an increasing demand for tap water, especially for high-quality water supply.

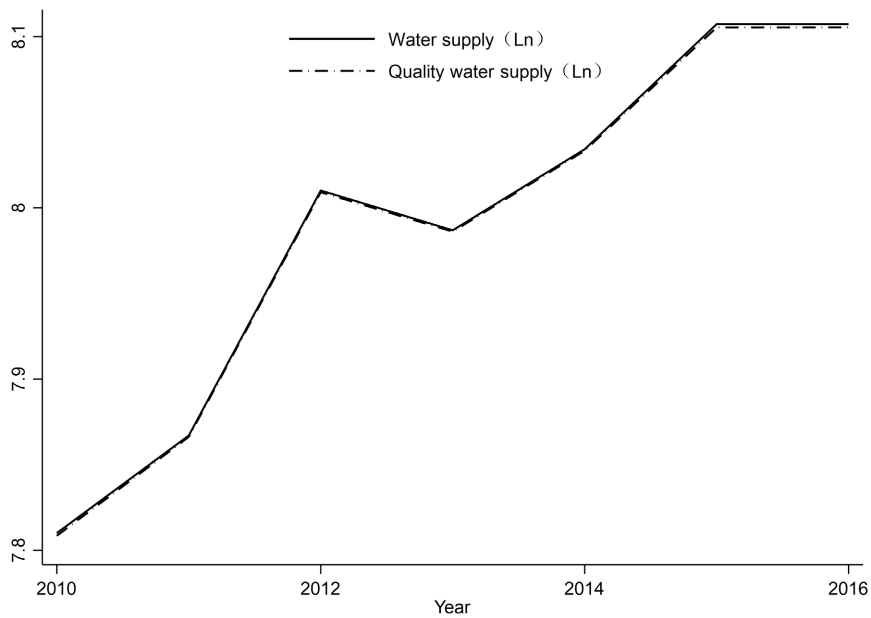

Figure 2. Quality water supply and water supply.

In the production model, this paper selects the main input factor variables including labor, capital, energy, and chemicals. Among them, the labor input factor is mainly measured by the number of employees, while the capital input factor of water supply utilities is mainly measured by the net value of fixed assets, denoted as Lnl and Lnk, respectively. In addition, the production and delivery processes of water supply products require power supply from electricity and the input of chemical agents. Therefore, key indicators such as electricity consumption and total chemical consumption are needed in the input factors, denoted as Lnele and Lnstuff. When analyzing the data nature of the relevant input factors, this paper finds that the original data of the chemical input and electricity consumption in the production function of water supply utilities are severely right-skewed, making it difficult to satisfy the assumption of normal distribution. The histogram and kernel density plot are shown in the left graph of Figure 3[4]. Therefore, this paper adopts a natural logarithm transformation to transform them into characteristics that conform to the assumption of normal distribution, as shown in the right graph of Figure 3.

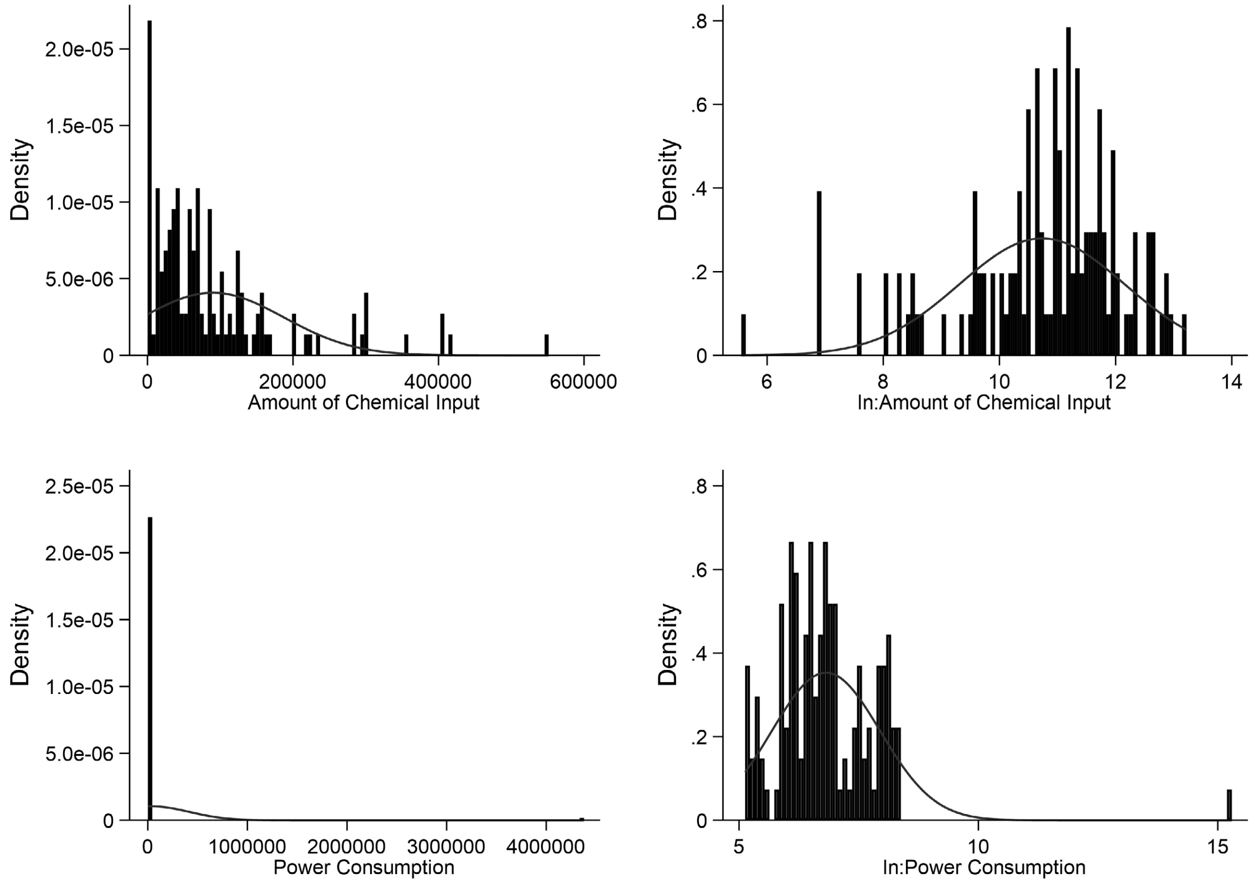

Figure 3. Comparison between original and transformed data.

4.2.2. Control Variables

The control variables in this paper mainly include the total designed capacity of water supply (Lnable), the population of urban water users (Lnpop), and the total length of enterprise pipelines (Lnpipe). These variables are selected to control the influences of factors such as the scale of water supply utilities, market demand, and infrastructure construction on the total water supply (Cabrera, 2008; Lin, 2005; Saal et al., 2013; Li, 2018).

[4]Due to space limitations, other variables in this paper are not shown and elaborated one by one.

4.2.3. Policy Variables

During our investigation in Shandong, we found that the key and major weakness of the implementation of "Smart Water" is focused on the construction of urban water supply emergency systems. Particularly during the rapid urban development, the effective guarantee and supply of water quality and quantity directly affect the quality of urban development. Therefore, based on the current situation in Shandong Province, this paper considers the completion of the corresponding intelligent emergency warning system as the assessment standard for the construction of "Smart Water" and designates this policy variable as *Intell*. In this case, if the water supply utilities in Shandong have completed the construction of smart water management from 2010 to 2016, the *Intell* indicator is set as 1; otherwise, it is set as 0.

In summary, this paper summarizes the input and output factor variables, control variables, and policy variables in **Table 2**.

Table 2. Descriptive statistics of the variables involved.

Variable	Variable meaning	Mean	Standard Error	Least Value	Crest Value	P25	P75
Lny	Quality water supply	7.99	0.90	6.04	10.17	7.40	8.59
Rate	Quality rate of comprehensive water quality is (%)	99.87	0.31	97.82	100	99.88	100
Lnele	Total power consumption	6.82	1.13	5.13	15.29	6.11	7.50
Lnstuff	Total amount of agent consumption	10.73	1.43	5.56	13.22	10.21	11.68
Lnk	Fixed assets-net value	9.57	1.17	6.35	12.13	8.82	10.27
Lnl	Number of employees	5.99	0.79	4.60	8.04	5.40	6.66
Intell	Whether the smart water mechanism is implemented	0.16	0.37	0	1	0	0
Lnnum	Number of water plants in the water supply utilities	0.89	0.60	0.00	2.20	0.69	1.39
Labor_structure	Technical personnel structure	0.31	0.35	0.03	3.73	0.20	0.37
Lnable	Total design capacity of water plant	2.77	0.83	0.69	5.12	2.28	3.18
Lnpuji	Water supply penetration rate	4.46	0.59	−0.29	5.23	4.43	4.61
Lngouxiao	Supply purchase and sale rate	2.92	0.35	2.15	3.66	2.64	3.25
Lnpop	Urban water consumption population (ten thousand people)	3.90	0.67	2.53	5.85	3.40	4.25
Lnpipe	Total pipe length	6.35	0.85	4.48	8.13	5.60	6.84

Notes: The author has compiled this table, with the numerical values rounded to two decimal places and the data processed using natural logarithm.

5. Analysis of Empirical Results

5.1. Comparison and Selection of Econometric Models

Based on the estimation strategy mentioned earlier, this paper first selects and tests the benchmark model. Following the recommendations of Greene (2003) (see also Greene, 2005b; Greene, 2005c), individual random effects and fixed effects regressions are conducted, and the benchmark model is determined using the Hausman test. From the statistical results in **Table 3**, both Model 1 and Model 2 exhibit significant features at a 99% confidence level. The Hausman test results indicate a chi-square statistic of 60.1 with a *P*-value of 0.0000, rejecting the null hypothesis. Therefore, the individual fixed effects model is found to be significantly superior to the random effects model. Hence, the individual fixed effects model will be adopted as the benchmark model in this study.

Table 3. Selection of econometric models and Hausman test.

Variable	Model 1	Model 2	Model 1 versus 2 coefficient comparison	
	Individual fixed-effect model	Individual random-effect model	Coefficient difference	Difference standard deviation
lnele	0.013 (0.853)	0.015 (0.904)	−0.001683	0.0096845
lnstuff	0.020* (1.756)	0.025** (2.148)	−0.0053944	0.0068508
lnk	0.051* (1.965)	0.055** (2.056)	−0.0041968	0.0124718
lnl	0.230*** (4.773)	0.211*** (4.609)	0.0187055	0.0148393
lnable	0.222*** (3.438)	0.349*** (6.519)	−0.1268862	0.0360327
lnpop	0.259*** (3.714)	0.328*** (5.008)	−0.0690207	0.0240264
lnpipe	0.069* (1.521)	0.100** (2.225)	−0.0315421	0.0036888
Constant term	3.757*** (11.400)	2.939*** (10.612)	-	-
Hausman Test (H_0: No significant difference between the coefficients)				
Statistics $\chi^2(6)$		41.78		
P price		0.0000		
Observed number	133	133	-	-

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

5.2. Estimation and Analysis of the Benchmark Model

After selecting the benchmark model, this study employs the fixed effects model for identification and estimation, and presents the corresponding results in Table 4. Firstly, examining the estimation results of the production model in Table 4 reveals significant positive relationships at a 5% confidence level between chemicals, labor, capital and input factors of water supply utilities in Shandong. This implies that a 1% increase in input factors will result in substantial increases of 2.6%, 10.1%, and 33.2% in chemicals, labor, and capital respectively. Furthermore, by employing the calculation formula for returns to scale[5], this paper computes a Return to Scale value of 0.459 for water supply utilities. The adoption of the C-D production function in this study reveals neutral characteristics of returns to scale concerning input and output quantities. Consequently, the water supply industry in Shandong demonstrates decreasing returns to scale as a whole, indicating that an equal proportional increase in chemicals, labor, and capital will result in a comparatively smaller proportional increase in water supply. From Table 4's perspective on marginal contributions, it is evident that the water supply industry in Shandong exhibits a labor-intensive nature with labor contributing approximately 33.2% marginally. Furthermore, significant positive effects are observed for the control variables, suggesting that market demand, enterprise water supply capacity, and infrastructure construction all contribute to the output of water supply.

Table 4. Estimation of the benchmark model and stochastic frontier models.

	Model 3	Model 4	Model 5
	Production model	Random cutting-edge model (management efficiency)	Random cutting-edge model (technical efficiency)
Lnele	0.017 (1.010)		
Lnstuff	0.026** (2.112)		
Lnk	0.101*** (3.972)		
Lnl	0.332*** (7.797)		
lnable	0.222*** (3.438)		
lnpop	0.259*** (3.714)		

[5]In general, the calculation of scale economies can be expressed as $\mathrm{RTS} = \left.\frac{\partial \ln f(\lambda x)}{\partial \ln \lambda}\right|_{\lambda=1}$. The frontier production function used in this article is homogeneous, so RTS can be calculated as $\sum \epsilon_i(x)$, where $\epsilon_i(x) = \frac{\partial \ln f(x)}{\partial \ln(x_i)}$ represents the elasticity of the respective input factor.

Continued

lnpipe	0.069* (1.521)		
$E(v_{it})$ or $E(\eta_i)$		0.362*** (4.566)	0.387*** (5.320)
Constant term	4.629*** (14.468)		
		σ_u	
Intell		−0.650* (−1.338)	−0.598* (−1.297)
Constant term		−1.506*** (−3.769)	−1.379*** (−3.985)
		σ_v	
Constant term		−3.085*** (−5.955)	−3.066*** (−6.392)
Observed number	133	133	133
The likelihood value	109.283	−45.241	−50.879

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Based on the estimation results from **Table 4**, it is evident that both management efficiency and technical efficiency exhibit significant characteristics in terms of their unconditional efficiency expectations. The exogenous shock variable (policy variable) demonstrates a significant impact at a 10% confidence level in both the stochastic frontier models for management efficiency and technical efficiency. This implies that the implementation of "Smart Water" in Shandong Province has substantial effects on technology and management. However, further exploration and analysis of the marginal effects generated by this implementation will be conducted in subsequent discussions, which are not elaborated upon here.

5.3. Calculation and Analysis of Management Efficiency and Technical Efficiency

Based on the estimation of production model and stochastic frontier model, this study employs formulas (4) and (6) to derive the levels of management efficiency and technical efficiency for water supply utilities in Shandong. **Table 5** presents a summary of the distribution characteristics of efficiency as well as information from distribution tests, which reflect the relationship between efficiency and inefficiency. The results of distribution tests reveal that both management efficiency and technical efficiency exhibit significant left-skewed distributions in Shandong's water supply utilities, with skewness values of −0.62 and −0.61 respectively. These skewness values are statistically significant at the 1% confidence level, indicating a pronounced deviation from normality towards lower efficiencies. This observation is further supported by **Figure 4**, where it can be observed that both peaks for management efficiency and technical efficiency are significantly shifted to the right compared to a standard normal distribution curve. Additionally, Table 5 shows that estimated inefficiency terms have significant right-skewed distributions for both management aspect (skewness = 0.91) and technical aspect (skewness = 0.93), with their respective skewness tests also exhibiting significance at the 1% confidence level[6].

Table 5. Distribution tests of management efficiency and technical efficiency.

Variable	Obs	Skewness	Partial *P* value	Peak *P*-value	Joint part	
					Fixed statistic	*P* price
Management efficiency	133	−0.62	0.0041***	0.0244*	11.32***	0.0035
Management inefficiency items	133	0.91	0.0001***	0.9975	13.02***	0.0015
Technical efficiency	133	−0.61	0.0048***	0.0220*	11.25***	0.0036
Technical inefficiency items	133	0.93	0.0001***	0.7590	13.64***	0.0011

Notes: This table was generated by the author using Stata 15.0. The estimated values of parameters and statistical measures are rounded to two significant figures after the decimal point; *P*-values are rounded to three significant figures after the decimal point; in the table, ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

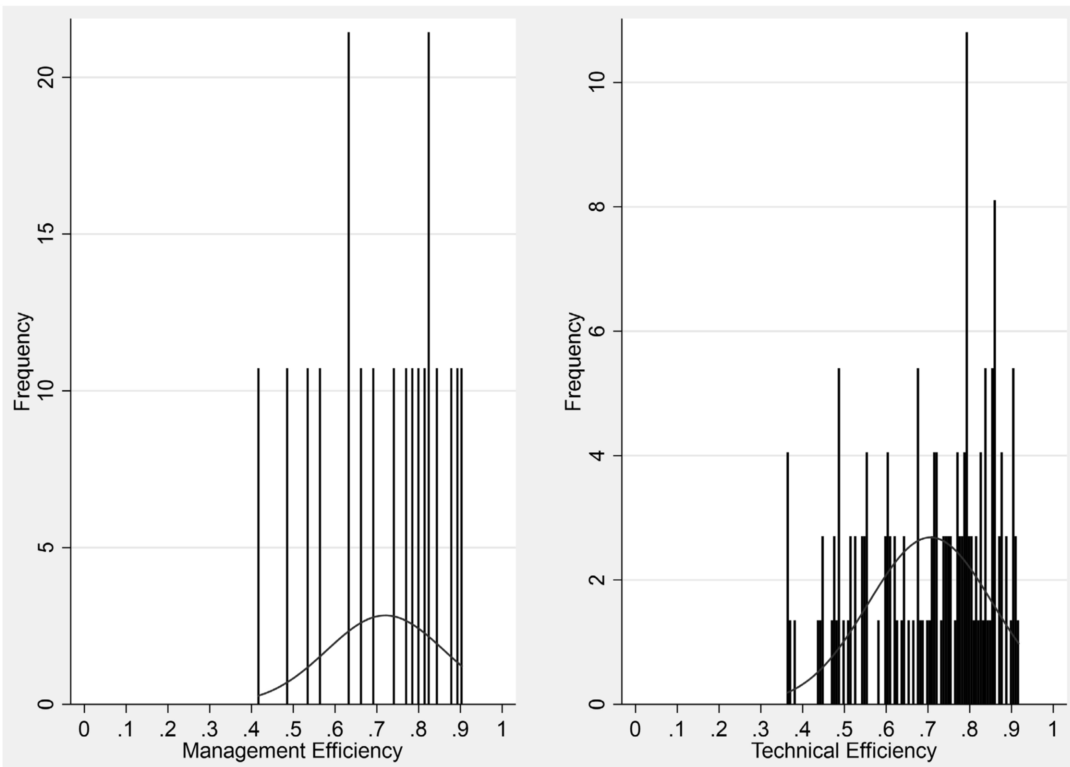

Figure 4. Distribution of management efficiency and technical efficiency.

[6]As this paper focuses more on efficiency values and distribution patterns, the distribution plot in Figure 5 is not presented or depicted.

Using the estimation strategies outlined in formulas (4), (6), and (7), this study derived the values of management, technical, and overall efficiency for water supply utilities in Shandong, as presented in **Table 6**. Based on the calculations (refer to **Table 6**), it can be observed that the management efficiency and technical efficiency of water supply utilities in Shandong exhibit a relatively similar pattern, with mean values of 70.6% and 72%, respectively. The range of values for management efficiency spans from 36.2% to 91.8%, while for technical efficiency, it ranges from 41.4% to 90.5%. Correspondingly, the mean value of overall efficiency is determined as 52.9%, with an efficacy range between 15% and 82.2%, slightly surpassing the national average calculated by Lin (2005).

Due to the utilization of different models for estimating technical efficiency, management efficiency, and overall efficiency, direct comparison of their dispersion using standard deviations becomes challenging. Hence, by considering the means and standard deviations presented in **Table 6**, the coefficients of variation for these three measures are calculated as 0.211, 0.196, and 0.365[7], respectively. It is evident that the fluctuation in overall efficiency surpasses that of technical efficiency and management efficiency, indicating relatively low variation in management efficiency within Shandong's water supply industry while highlighting technical efficiency and technological innovation as key factors contributing to differences among utilities. In practice, as a vital sector of municipal public services, enhancing technical capabilities in water supply utilities (including communication technology, scheduling technology, data collection and monitoring control technology) such as machine learning techniques or neural networks alongside edge computing technologies will progressively lead to the formation of clusters characterized by enhanced efficiencies[8]. This implies that adopting new technologies will result in widening gaps between those who do not adopt them; however, utilities embracing similar new technologies will gradually converge towards improved efficiencies ultimately forming an aggregated characteristic or community with clustered efficiencies.

Table 6. Management, technical, and overall efficiency of water supply utilities in Shandong.

Variable	Obs	Mean	Standard error	Least value	Crest value
$\text{Tech}_{\text{efficiency}}$	133	0.706	0.149	0.362	0.918
$\text{Man}_{\text{efficiency}}$	133	0.720	0.141	0.414	0.905
$\text{Overall}_{\text{efficiency}}$	133	0.529	0.193	0.150	0.822

Notes: This table was generated by the author using Stata 15.0; values are rounded to three significant figures after the decimal point.

[7]The calculations here mainly utilize the coefficient of variation formula, which is calculated as the standard deviation divided by the mean.

[8]In the subsequent analysis of the implementation of "Smart Water" in Shandong Province, this "clustering" phenomenon can be observed.

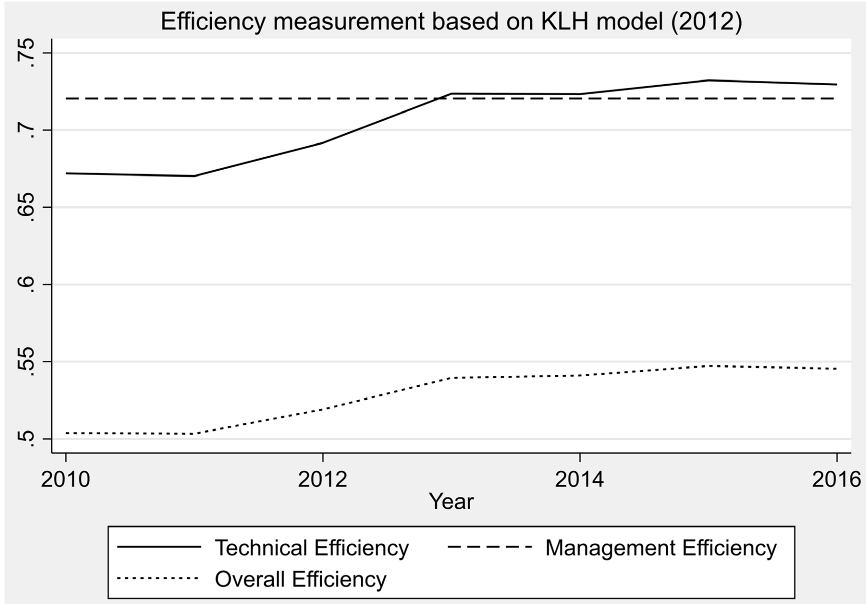

Figure 5. Average level changes of technical and management efficiency in Shandong water supply utilities from 2010 to 2016.

From the annual efficiency changes of water supply utilities in Shandong (Refer to **Figure 5**), it can be divided into two stages: the first stage is the rapid development stage (2010-2013), and the second stage is the consolidation stage (2013-2016). Specifically, in the rapid development stage of water supply utilities in Shandong (2010-2013), the technical efficiency increased from 66.5% to 77.5%, while the management efficiency remained constant at 77.0% due to the assumption of time invariance in the model[9]. The overall efficiency increased from 49.3% in 2010 to 60.3% in 2013. Looking at the efficiency changes in the first stage, the average annual growth rate of technical and overall efficiency in Shandong Province's water supply utilities was only 3.7%, which is significantly higher than the 2.3% efficiency increase calculated for the UK's water supply industry by Saal and Parker (2001) In 2013, Shandong Province began implementing the "Guidelines for Urban Water Supply Security Assessment and Evaluation in Shandong Province (Trial)", which increased the daily and monthly inspection indicators for water supply utilities and enhanced urban water supply monitoring capabilities, thereby consolidating the water supply security capabilities of utilities. Therefore, starting from 2013, water supply utilities in Shandong Province officially entered the consolidation stage (2013-2016). In this stage, the technical efficiency increased from 77.5% to 79.0%, the management efficiency remained at 77.0%, and the overall efficiency increased from 59.9% in 2013 to 60.8% in 2016. Compared to the rapid development stage, the average annual growth rate of technical and overall efficiency in Shandong Province's water supply utilities in this stage was only 0.3%. The significant slowdown in efficiency growth can be attributed to two

[9]Kumbhakar et al. (2012), when measuring managerial efficiency of American firms, found that managerial efficiency is difficult to change rapidly in the short term, indicating its time-invariant characteristics.

reasons: firstly, the water quality was included as an important assessment indicator for the operation of water supply utilities in Shandong Province, which provided insufficient stimulus for technological innovation. Secondly, due to the substantial infrastructure development in the rapid stage, the level of technical efficiency was already relatively high, limiting the scope for efficiency improvement and resulting in a significant decrease in the rate of efficiency growth.

5.4. Robustness Tests

Table 7. Robustness test.

	Model 4	Model 5	Model 6
	Benchmark model	Overall mean (PA) estimate	MLE estimate
lnele	0.013	0.014	0.014
	(0.853)	(0.953)	(0.953)
lnstuff	0.020*	0.022**	0.022**
	(1.756)	(2.048)	(2.032)
lnk	0.051*	0.052**	0.052**
	(1.965)	(2.058)	(2.054)
lnl	0.230***	0.219***	0.219***
	(4.773)	(4.932)	(4.908)
lnable	0.222***	0.320***	0.320***
	(3.438)	(6.006)	(5.583)
lnpop	0.259***	0.315***	0.315***
	(3.714)	(4.970)	(4.897)
lnpipe	0.069	0.090**	0.090**
	(1.521)	(2.094)	(2.071)
Constant term	3.757***	3.156***	3.156***
	(11.400)	(11.326)	(10.018)
		σ_u	
Constant term			0.258***
			(4.992)
		σ_e	
Constant term			0.117***
			(14.582)
N	133	133	133
ll			35.640

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

To prevent the issue of spurious regression in the previous estimation, this paper recalculates using the Population Average (PA) estimation technique and the Maximum Likelihood Estimation (MLE) technique, as shown in Table 7. By comparing models 6 to 8, the significance and sign of the coefficients for the selected core input variables (labor and capital) and other input factors remain unchanged. Therefore, it can be inferred that the estimation model adopted in this paper exhibits robustness.

6. Mechanism Analysis of the Impact of "Smart Water" on Management and Technical Efficiency

6.1. Marginal Effect Analysis of "Smart Water" Policy

Based on the calculation and estimation of the KLH model in the previous section, this paper obtained the levels of technical, management, and overall efficiency of water supply utilities in Shandong Province. However, in reality, since 2010, some areas of Shandong Province have started implementing the "Smart Water" construction, but the extent of its impact on water supply utilities remains uncertain. This is a topic of concern for the author of this paper as well as government departments. Therefore, based on the previous calculations, this paper uses the estimation strategy's formula for estimating the marginal effect of the policy. The formula is as follows:

$$\begin{aligned}\frac{\partial E(I)}{\partial z} &= \beta_1[z]\left\{1-\Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]-\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^2\right\} \\ &\quad +\beta_2[z]\frac{\sigma_I}{2}\left\{\left(1+\Delta^2\right)\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]+\Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^2\right\}\end{aligned} \tag{10}$$

And

$$\begin{aligned}\frac{\partial D(I)}{\partial z} &= \frac{\beta_1[z]}{\sigma_I}\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]\left[E(I)^2-D(I)\right] \\ &\quad +\beta_2[z]\sigma_I^2\left\{1-\frac{1}{2}\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]\left\{\Delta+\Delta^3+\left(2+3\Delta^2\right)\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]+2\Delta\left[\frac{\phi(\Delta)}{\Phi(\Delta)}\right]^2\right\}\right\}\end{aligned} \tag{11}$$

Among them, Formula (10) reflects the relationship between the mean of inefficiency and the policy variable, while Formula (11) reflects the relationship between the volatility of efficiency and the policy variable. If $\frac{\partial E(I)}{\partial z}<0$ and $\frac{\partial D(I)}{\partial z}<0$, it indicates that the implementation of the policy will restore efficiency losses and effectively reduce their uncertainty. Combining the calculations of Formulas (10) and (11), this paper summarizes the marginal effect results of implementing the "Smart Water" construction in Shandong Province in Table 8. From the results of parameter estimation, the impact of the "Smart Water" measures on management efficiency and technical efficiency is significant at a 10% confidence level, indicating the strong research significance of the marginal effect of the policy variable. Looking at the marginal effect of efficiency loss of the policy variable, both the inefficiency levels of technology and management show a negative relationship, i.e., $\frac{\partial E(I)}{\partial z} = -0.117$ and -0.115. This indicates that the implementation of the "Smart Water" construction in Shandong Province will effectively reduce the efficiency losses of technology and management by approximately 11.7% and 11.5%, respectively, thereby effectively improving the levels of management and technical efficiency. At the same time, we find that the volatility of efficiency also shows a significant negative relationship with policy implementation, i.e., $\frac{\partial D(I)}{\partial z} = -0.048$ and -0.051. This indicates that policy implementation will effectively reduce the dispersion of efficiency distribution, making the efficiency of water supply utilities in Shandong more concentrated. In summary, we find that the implementation of the "Smart Water" construction in Shandong Province has a significant effect on improving both technical efficiency and management efficiency, with an approximate improvement of 11.7% and 11.5%, respectively. This is mainly due to the content of the "Smart Water" construction, which includes production and operation monitoring, emergency warning technology aimed at improving water quality. On the other hand, the construction project is mainly based on communication technology, computing technology, and office systems, and the corresponding system construction will effectively improve the management efficiency of utilities. At the same time, we also find that due to the implementation of the "Smart Water" construction in Shandong Province, the dispersion of enterprise efficiency has significantly decreased, showing a trend of concentrated efficiency. This is mainly because although the "Smart Water" construction is mainly reflected in the hardware environment, the project can fully comb through technical resources, identify and fill the gaps in technology and management efficiency of utilities, gradually narrowing the efficiency gap between utilities, and thus exhibiting convergence characteristics.

Table 8. Impact of "Smart Water" on the improvement of management and technical efficiency.

Efficiency Type	Policy Variable (z)	Parameter estimation	Marginal effect of efficiency loss	
			$\frac{\partial E(I)}{\partial z}$	$\frac{\partial D(I)}{\partial z}$
Management efficiency	Intell (smart water)	−0.650* (−1.338)	−0.117	−0.048
Technical efficiency		−0.598* (−1.297)	−0.115	−0.051

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Building upon the comprehensive analysis in the previous sections, this paper further visually illustrates the distribution of different efficiency levels under the influence of "Smart Water" by plotting Figure 6. By comparing the two sides of Figure 6, it can be observed that the impact of implementing "Smart Water" on improving management efficiency is slightly stronger than that on technical efficiency. Specifically, compared to utilities that have not implemented "Smart Water," those that have implemented the project see an average increase in management efficiency from 67.9% to 83.8%, and an average increase in technical efficiency from 65.5% to 81.5%. Looking at the distribution characteristics in Figure 6, the kernel density curve becomes steeper after policy implementation, transforming from a bimodal feature to a unimodal distribution with a higher concentration. This indicates that the policy not only significantly improves the level of technical efficiency but also shows a positive market response to the "Smart Water" construction, gradually forming a highly concentrated block-like structure of efficiency. Therefore, it can be concluded that the government's implementation of the reform approach of "Smart + Public Utilities" can effectively stimulate the enthusiasm for technological investment and management innovation in utilities, enhance the technical efficiency of urban public industries, and encourage municipal utilities to improve their technical efficiency to maintain market competitiveness.

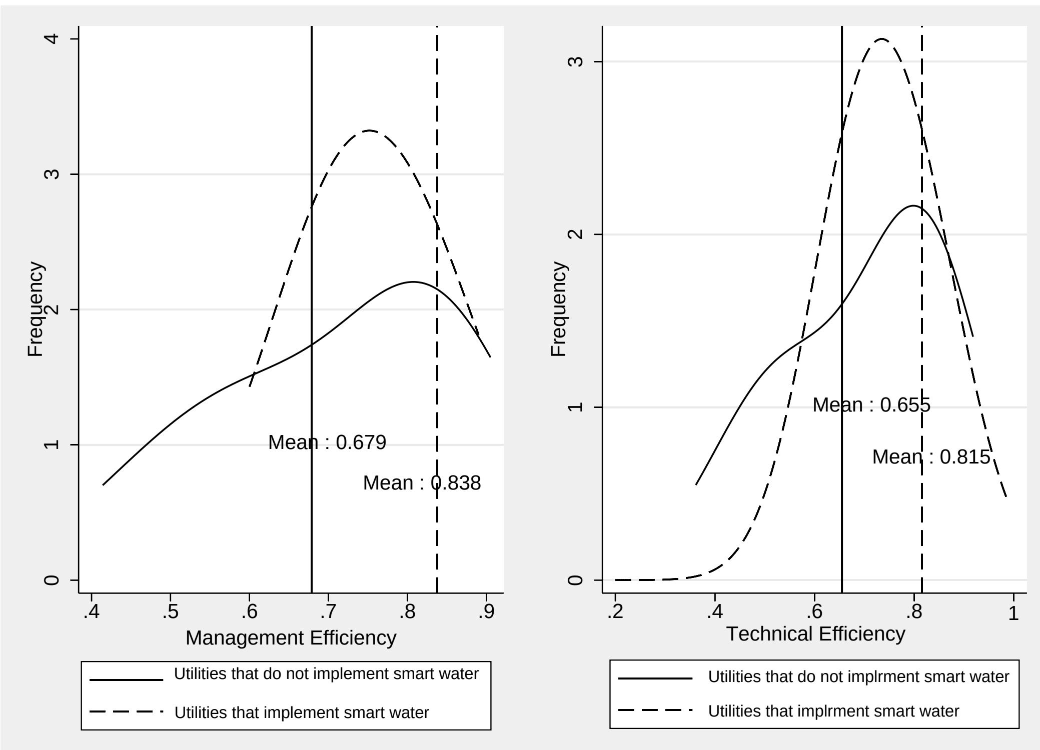

Figure 6. Impact of "Smart Water" implementation on the improvement of management and technical efficiency in water supply utilities.

6.2. Mechanism Analysis of the Impact of "Smart Water" Construction on Technical and Management Efficiency

Although the marginal effects of "Smart Water" construction on the technical efficiency and management of water supply utilities have been calculated in the previous section, it is still worth exploring in depth the pathways through which these marginal effects improve the efficiency of utilities. This paper attempts to analyze the mediating mechanism of the technical and management efficiency of water supply utilities by drawing on the methods and ideas provided by Wen et al. (2004) for testing the mediating effect.

6.2.1. Mediation Effects Estimation in Technical Efficiency

Table 9. Estimation of the mediating effect of technical efficiency.

	Quantitative mediating effect of water plant			Mediating effect of technical ratio		
	$Tech_{efficiency}$	$Tech_{efficiency}$	lnnum	$Tech_{efficiency}$	$Tech_{efficiency}$	Labor_structure
Intell	−0.011	0.006*	0.324**	0.005	0.006*	−0.458
	(−0.391)	(2.203)	(2.283)	(0.176)	(2.203)	(−1.554)
lnnum	0.050***					
	(2.668)					
Labor_structure				−0.002		
				(−0.157)		
lngouxiao	0.014	0.017	0.058	0.006	0.017	0.058
	(0.698)	(0.820)	(0.546)	(0.267)	(0.820)	(0.266)
lnpuji	0.007	0.008	0.014	0.008	0.008	−0.005
	(1.235)	(1.325)	(0.480)	(1.298)	(1.325)	(−0.082)
lnable	0.071***	0.076***	0.082	0.082***	0.076***	−0.221
	(3.373)	(3.470)	(0.723)	(3.457)	(3.470)	(−0.930)
lnpop	0.001	0.030**	0.580***	0.027*	0.030**	−0.213
	(0.046)	(2.019)	(7.582)	(1.714)	(2.019)	(−1.371)
lnpipe	−0.057***	−0.047***	0.207***	−0.049***	−0.047***	−0.009
	(−4.699)	(−3.944)	(3.335)	(−3.922)	(−3.944)	(−0.074)
Constant term	0.855***	0.690***	−3.299***	0.728***	0.690***	2.159*
	(7.170)	(6.568)	(−6.045)	(6.486)	(6.568)	(1.955)
Individuality	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
N	130	130	130	117	130	117

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

According to the estimation results presented in **Table 9**, while controlling for other variables, it is observed that an increase in the quantity of water plants significantly enhances the technical efficiency of water supply utilities at a confidence level of 1%. Furthermore, considering the significant levels of Intell coefficients in columns 2 and 4 of **Table 9**, it can be inferred that the quantity of water plants within water supply utilities plays a crucial role as a fully mediating effect[10]. Consequently, this study concludes that implementing "Smart Water" infrastructure enables water supply utilities to expand their operations by increasing both the quantity and scale of their water plants, thereby leading to substantial improvements in their technical efficiency. In light of **Figure 2** and taking into account the actual situation and trends observed, it becomes evident that the decline in Shandong Province's number of water supply utilities is primarily attributed to integration efforts facilitated through "Smart Water" initiatives. These endeavors empower these utilities with digital technologies for systematic management. This phenomenon presents a significant scale effect in the water industry in Shandong, effectively enhancing the technical efficiency of utilities. Simultaneously, this study also investigates whether the implementation of "Smart Water" can substantially enhance technical efficiency by increasing the proportion of skilled personnel (Acemoglu, 1997). Based on the findings presented in columns 5 to 7 of **Table 9**, it is evident that implementing "Smart Water" in Shandong does not significantly improve technical efficiency through an increase in skilled personnel. This is primarily attributed to state-owned nature of water supply utilities, which often impose certain restrictions and constraints on personnel numbers and adjustments. Consequently, there has been limited optimization and adjustment regarding the composition of skilled personnel. It can be observed that adjusting human resources levels within public utilities such as water supply is relatively challenging due to industry-specific influences. Therefore, revitalizing utility operations through innovative corporate systems becomes a crucial area for future governmental attention.

6.2.2. The Mediating Mechanism in Terms of Management Efficiency

Based on the estimated results in column 2 of **Table 10**, while controlling for other variables, it is observed that an increase in the quantity of water plants significantly hampers the management efficiency of water supply utilities at a 5% confidence level. Furthermore, considering the significant levels of Intell coefficients in columns 2 and 4 of **Table 10**, it suggests that the presence of water plants within water supply utilities obscures management efficiency by accounting for approximately 0.48% of the total effect[11]. This highlights a substantial challenge posed by "Smart Water" construction towards maximizing plant quantity and subsequently reducing management efficiency levels within water supply utilities. Considering practical implications, expansion efforts in Shandong Province's water supply utilities are expected to inevitably lead to a decline in management efficiency. However, when considering the impact on technical efficiency mentioned earlier, it becomes evident that "Smart Water" can effectively compensate for the decline

[10]The main basis for determining the complete mediating effect comes from the testing strategies provided by Wen et al., 2004. This paper won't go into detail here.

[11]The judgment criteria and calculation formulas for the masking effect mainly come from the testing strategies provided by Wen et al., 2004. This paper won't go into detail here.

in management efficiency by enhancing technical efficiency, thereby leading to an overall improvement in efficiency. Additionally, as indicated by the results presented in columns 5 to 7 of **Table 10**, labor structure acts as a partial mediator. The coefficient of labor_structure exhibits a significant positive effect at a confidence level of 10%, with its mediating role accounting for approximately 12.12% of the total effect. It is apparent that human capital plays a pivotal role in management efficiency due to its active involvement in system operations and the establishment of remote control for water plants within the framework of "Smart Water". Therefore, highly skilled personnel are essential for translating hardware technology into adaptable management practices. This finding emphasizes that water utilities with high management efficiency possess distinct advantages concerning human capital quality.

Table 10. Estimation of the mediating effect of management efficiency.

	Quantitative mediating effect of water plant			Mediating effect of technical ratio		
	$Man_{efficiency}$	$Man_{efficiency}$	lnnum	$Man_{efficiency}$	$Man_{efficiency}$	Labor_structure
Intell	0.034***	0.034***	0.324	0.034***	0.034***	0.458
	(6.9e+13)	(9.6e+13)	(1.100)	(2.2e+13)	(9.6e+13)	(1.174)
lnnum	−0.000**					
	(−2.029)					
Labor_structure				0.009*		
				(1.378)		
lngouxiao	−0.000	−0.000*	0.058	0.000**	−0.000	0.117
	(−0.992)	(−1.982)	(0.401)	(2.370)	(−1.964)	(2.894)
lnpuji	−0.000	−0.000	0.014	−0.000	−0.000	−0.005
	(−0.102)	(−0.398)	(0.455)	(−1.164)	(−0.398)	(−0.490)
lnable	0.000	0.000	0.082	0.000*	0.000	−0.221
	(0.199)	(0.490)	(0.457)	(1.934)	(0.490)	(−0.751)
lnpop	0.000	−0.000	0.580*	0.000	−0.000	−0.213
	(0.640)	(−0.526)	(1.874)	(1.317)	(−0.526)	(−0.772)
lnpipe	0.000**	0.000	0.207	−0.000	0.000	−0.009
	(2.117)	(1.434)	(1.498)	(−0.223)	(1.434)	(−0.128)
Constant term	0.830***	0.830***	−3.299**	0.830***	0.830***	2.159
	(7.4e+14)	(7.3e+14)	(−2.523)	(2.2e+14)	(7.3e+14)	(1.558)
Individuality	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes
N	130	130	130	117	130	117

Notes: The parameter estimates are rounded to three significant figures after the decimal point, while the statistics in parentheses are also rounded to three significant figures. In the table, significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

7. Conclusion and Policy Recommendations

The water supply industry, as a crucial component of municipal public utilities, plays a pivotal role in determining the spatial and scale aspects of urban development[12]. In this study, utilizing survey data from water supply utilities in Shandong Province between 2010 and 2016, we employed the KLH model to assess both management efficiency and technical efficiency. Subsequently, we analyzed the impact of implementing "Smart Water" on the management and technical efficiency of water supply utilities in Shandong Province. Following our research endeavor, we have obtained the following findings:

Initially, the technical and management efficiency of water supply utilities in Shandong Province stood at 70.6% and 72%, respectively, resulting in a composite efficiency of 52.9%. Analyzing the evolution of comprehensive efficiency over time, Shandong's water supply utilities underwent distinct phases characterized by rapid development and consolidation, with an average growth rate of approximately 3.2% during the former phase. Subsequently, the implementation of "Smart Water" in Shandong Province is projected to enhance average technical and management efficiencies by 11.7% and 11.5%, respectively, while also fostering a trend towards concentration in both aspects across water supply utilities within the province. From a mediating mechanism perspective, it is observed that the construction of scaled-up water supply utilities primarily influences technical efficiency enhancement; however, for management efficiency improvement, scaling up utilities may have a masking effect due to adjustments made to the technical personnel structure aimed at leveraging high-level technical expertise for transforming technical proficiency into flexible management capabilities.

In conclusion, the government can effectively harness technological input and management innovation by implementing the reform approach of "Smart + Public Utilities", thereby enhancing the technical efficiency of urban public utilities and enabling municipal utilities to improve their technical efficiency and maintain market competitiveness. Therefore, this study proposes the following policy recommendations to optimize the role of smart water system and further enhance management efficiency: streamlining and standardizing business processes, harmonizing smart water standards, providing technology and talent support, and fostering an environment conducive to smart water development. This study offers valuable policy insights for subsequent decision-making.

1) Strengthen and optimize operational procedures in the utilities sector. Conventional enterprise management predominantly depends on managers' experience to accomplish management objectives by coercion or physical strength,

[12]General Secretary Xi Jinping pointed out in his important discourse on ensuring water security that we must adhere to the principle of adjusting measures according to local conditions and manage water resources based on their availability. We should plan cities and industries based on water availability and consider the relationship between population, economy, and resource environment from the perspective of ecological civilization construction. It is crucial to strengthen the rigid constraints on water resources and the environment. This highlights the decisive role of the water supply industry in urban development.

which does not fulfill the demands of contemporary enterprise management systems and goes against the trend of enhancing efficiency through intellectual advancement. The problem of benefits is best exemplified by the enhancement of management efficiency. The process of migrating from comprehensive to intensive management serves to improve efficiency (De Witte and Geys, 2011). This perspective is consistent with the study findings reported in this publication. As a result, there is currently a greater emphasis on improving both the amount and the standard of information, with the goal of increasing management efficiency through the use of more extensive information resources. In order to achieve this goal efficiently, it is crucial to thoroughly simplify and improve current utility management procedures based on the features of information-intensive management, while also ensuring that they are in conformity with the guiding principles of such practices.

2) Standardized architectural guidelines for smart water systems in water supply utilities are crucial to facilitate the integration and merging of diverse information sources within these utilities. Unified management and analysis enable the acquisition of valuable information, facilitating effective decision-making. Hence, the implementation of intelligent water systems requires the resolution of information obstacles within utility companies and the attainment of smooth data integration. This needs the creation of unified data standards, construction standards, and administration protocols while supporting uniform collection of multiple data formats by water supply utilities to build a centralized big data center. Standard interfaces are created to enable the circulation, exchange, and sharing of data between various business systems. This helps eliminate isolated pockets of information and ultimately leads to a unified enterprise information system, enhancing overall management efficiency.

3) Facilitate the widespread adoption and utilization of developing information technology. To attain smart water, it is important to fully exploit emerging technologies such as big data, cloud computing, and the Internet of Things, while embracing algorithmic developments like machine learning, neural networks, and edge computing. Integrating databases from different sources in water supply utilities allows for in-depth analysis of water service data, enabling the implementation of business operations in various management scenarios. Improving operational management capabilities will give utilities new abilities that promote opportunities for increased profits by optimizing costs and enhancing efficiency.

4) Enhance the training of informationization and comprehensive business talents. Human beings are consistently the primary driving force behind productivity, and placing importance on the role of humans is always justified. All personnel inside the organization, regardless of their position, must possess a comprehensive comprehension of enterprise management informatization and establish a unanimous agreement from the highest to the lowest levels. The pace and success of enterprise informationization construction are determined by the extent of senior management's involvement, the level of passion displayed by middle-level

management, and the attitude of employees. The creation and management of smart water involves significant understanding not only in informationization but also in production and operation management within water supply utilities. The increasing advancement of smart water technology necessitates a greater emphasis on comprehensive talent training, as it directly impacts the effectiveness of smart water systems. There is a pressing need for enhanced training in various sectors such as industry management, local government administration, and water supply utilities. This training should focus on integrating information technology with effective management practices. The goal is to develop a skilled workforce for smart water systems and to strengthen business training programs for professionals involved in constructing, operating, and managing such systems.

Funding

Supported by Significant Project of the National Social Science Foundation of China "Study on the Development of New Energy Regulatory System and Optimization of Regulatory Policies in China under the Double Carbon Target" (Approval No. 23 & ZD102), the National Natural Science Foundation project "Evaluation of China's New Energy Subsidy Policy, Precision Subsidy Mechanism, and Incentive Regulation" (Approval No. 72003168), Significant Project of the National Social Science Foundation of China "Study on the Development of New Energy Regulatory System and Optimization of Regulatory Policies in China under the Double Carbon Target" (Grant No. 23 & ZD102) and the project commissioned by the Shandong Urban Water Supply and Drainage Water Quality Monitoring Center, "Assessment of the Impact of Informationization in the Urban Water Supply Industry on Management Efficiency and Technical Efficiency of Water Supply Enterprises" (Approval No. 2022hx119).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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