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The Influence of Urban Digital Development Index on Water Resource Utilization Efficiency—Based on System GMM Model Test

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Abstract

This study employs panel data for 275 Chinese cities from 2011 to 2021. Water use efficiency is measured as an aggregate city-level indicator via stochastic frontier analysis, while the level of digital economy development is quantified using principal component analysis. We then employ the system generalized method of moments to investigate the causal relationship between the digital economy and urban water use efficiency, and further identify industrial structure upgrading as the mediating role through which the digital economy affects water efficiency. The main findings are as follows: (1) The digital economy has a significant positive impact on urban water use efficiency. (2) Regional heterogeneity analysis shows that the digital economy presents a stronger positive effect on water use efficiency in eastern regions than in central and western regions. (3) Exploratory mechanism analysis indicates that industrial structure upgrading serves as the mediating role through which the digital economy improves urban water use efficiency. Based on the empirical findings, this paper draws targeted policy implications.

Keywords: digital economy; water use efficiency; industrial structure upgrading; system generalized method of moments model; water resources management

1. Introduction

Water represents the source of life, the foundation of production, and the core of ecological security. Water scarcity has emerged as a critical bottleneck restricting the sustainable development of the global economy [1]. China is characterized by insufficient total water resources and severely uneven spatiotemporal distribution. With the continuous advancement of industrialization and urbanization, the country is under the dual pressures of resource-induced water scarcity and structural water shortage [2]. Against this background, improving water use efficiency and realizing the sustainable utilization of water resources has become a major and urgent challenge to be addressed.

Traditional water use efficiency evaluation has long focused on input–output relationships to support economic growth objectives [3]. Driven by the new development philosophy, however, water use efficiency has evolved from a singular economic objective into a comprehensive criterion for high-quality development. As a new economic form

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empowered by modern information and network technologies, the digital economy has become a pivotal force in reshaping global resource allocation, economic structure, and competitive patterns. Supported by digital transformation and the widespread application of big data, Internet of Things, and intelligent monitoring technologies, the paradigm of water use efficiency evaluation is undergoing a profound shift [4–6]. Against this backdrop, the digital economy not only fuels socioeconomic development but also provides viable solutions to long-standing water resource management dilemmas in China [7]. By optimizing resource management mechanisms and constructing digital trading platforms, digitalization facilitates cross-sectoral resource allocation and integration [8]. With deepening penetration, digital technologies exert profound effects on technological innovation, resource allocation, and pollution mitigation. These factors are all core determinants of water use efficiency [9,10]. For example, advances in big data analytics and artificial intelligence drive more intelligent water resource management [11,12]. In turn, digitally enabled management systems optimize water allocation, reduce waste, and improve overall efficiency [13,14].

Beyond direct efficiency improvements, the digital economy is transforming industrial production models and advancing sustainability. It pushes industries to transition from conventional high-consumption, high-pollution patterns toward resource-efficient and low-carbon production systems, thereby reducing water pollution and further lifting water use efficiency [15]. Notably, the digital economy also acts as a key driver of industrial structure upgrading, suggesting that its influence on water use efficiency may operate indirectly through reshaping industrial development patterns and optimizing sectoral resource dependence [16].

Given China's vast territory and uneven digital economy development across provinces, municipalities, and autonomous regions, whether digital economy growth can effectively improve water use efficiency and through which specific mechanisms remains to be systematically investigated.

Although existing studies have investigated the impacts of digital development on water use efficiency, critical research gaps remain unaddressed. First, most studies treat water use efficiency solely as technical efficiency and focus predominantly on technological pathways, emphasizing only the direct water-saving effects of digital technologies such as intelligent monitoring, precision irrigation, and pipeline optimization, while rarely exploring the mechanisms for improving comprehensive water use efficiency from the perspectives of urban industrial structural transformation and resource allocation optimization [17–19]. Urban-level water use efficiency is inherently a composite indicator that encompasses both real water savings driven by technological progress within industries and reductions in water intensity resulting from industrial structural upgrading [15]. The digital economy has emerged as a core channel for enhancing water use efficiency by facilitating the transition of industries toward low-water-consumption and high-value-added models, and addressing this research gap constitutes the core objective of the present study. Second, most studies remain at the provincial level, with limited dynamic analysis of large samples across cities [20]. Third, the majority of studies employ static models such as ordinary least squares (OLS), which struggle to handle reverse causality and dynamic lag effects, resulting in weak causal identification.

To this end, based on the realistic background of water resource scarcity in Chinese cities and the rapid penetration of the digital economy, this paper systematically reviews existing literature gaps and conducts empirical analysis focusing on the real impact of the digital economy on urban water use efficiency, regional disparities, and internal transmission mechanisms. The marginal contributions of this study are primarily reflected in three aspects: First, in terms of research perspective, the paper clearly distinguishes between

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technological water-saving effects and structural transformation effects, breaking through the limitation of the existing literature that only focuses on direct technological water conservation. It emphasizes that industrial structure upgrading serves as the core channel for improving water efficiency in the digital economy, aligning more closely with the true essence of urban comprehensive water efficiency. Second, in terms of research design, based on large-sample panel data from 275 cities, the study employs System Generalized Method of Moments (System GMM) for dynamic causality identification, effectively addressing issues such as missing variables, reverse causality, and serial correlation, thereby enhancing the reliability of conclusions. Third, in terms of policy implications, the study examines regional heterogeneity across eastern, central, and western regions, demonstrating that the digital economy's impact depends on regional development foundations. This provides empirical evidence for formulating differentiated digital water-saving policies.

2. Theory and Hypothesis

2.1. The Overall Impact of the Digital Economy on Urban Water Use Efficiency

American scholars first proposed the concept of the digital economy and used numerous examples to show that it centers on information digitization. Some experts define the digital economy as economic activities connected to digital technologies and information systems [21]. The digital economy demonstrates "ubiquity" and "penetration" across industries.

From the perspective of resource allocation, the digital economy improves water use efficiency through two logically distinct channels. The intra-sectoral channel optimizes the allocation of water, capital and labor within the same industry to raise technical efficiency. The inter-sectoral channel drives factors to flow across industries and improves structural efficiency by adjusting industrial proportions across industries.

On the one hand, the digital economy directly improves water use efficiency through intra-sectoral resource allocation optimization. At the macro level, intelligent technologies and big data analytics optimize production resource allocation across sectors, driving the transformation of manufacturing toward low-consumption and low-pollution models [22]. Advanced water management systems and automation technologies further promote efficient water use throughout production processes. At the micro level, digital technologies, including 5G and blockchain, enable agricultural firms to reduce factor inputs while improving machinery efficiency and environmental performance. Industrial enterprises can optimize factor input structure, accelerate green technological progress, and lower water consumption per unit output [23].

From the perspective of environmental governance, digital technologies strengthen environmental supervision and public participation [24]. Digital water management platforms support real-time monitoring and refined governance, reducing water waste at the source. Meanwhile, digital media helps enhance public water-saving awareness and household water recycling, facilitating the adoption of eco-friendly lifestyles [25]. Emerging digital tools such as big data, artificial intelligence, and the Internet of Things further enable intelligent monitoring, precise irrigation, pipeline leak detection, and real-time water allocation, which directly improve water use efficiency [10].

On the other hand, the digital economy exerts an indirect effect by driving inter-sectoral structural transformation. Digital transformation tends to push the economic structure toward technology-intensive, low-water-consumption, and high-value-added sectors, thereby reducing the overall water intensity of the city [26]. Since different industries differ greatly in water consumption per unit output, such structural shifts can effectively lift the city's comprehensive water use efficiency.

Together, these two channels generate a positive total effect of the digital economy on water use efficiency. Therefore, this paper proposes Hypothesis 1.

H1. *The digital economy effectively improves water use efficiency.*

2.2. Indirect Impact of Digital Economy on Urban Water Use Efficiency

Against the deep integration of digital technologies and traditional industries, digital development directly lifts technical efficiency by optimizing intra-industry resource allocation. It also drives industrial structure upgrading through cross-sectoral resource reallocation. This structural pathway is underpinned by the dual paradigms of industrial digitization and digital industrialization and reflects a typical inter-sectoral resource reallocation effect rather than intra-sectoral technical improvement [7].

Industrial digitization, with data empowerment as its core support and value realization as its main thread, facilitates comprehensive digital transformation across the entire industry chain. This enhances production quality and efficiency, thereby accelerating industrial restructuring [15]. Digital industrialization, by providing essential digital technologies and products, achieves automated and intelligent production processes, improves production efficiency and resource allocation effectiveness, while fostering innovative business models [26]. This stimulates real economic growth, steering it toward high-tech, high-efficiency, low-energy consumption, and low-pollution development.

The digital economy reduces excessive reliance on natural resources and lowers pollution emissions during production [27]. By empowering traditional industries, digital transformation alleviates resource misallocation and improves factor utilization efficiency [28]. As industrial structure upgrades, the proportion of high-water-consuming industries gradually decreases, while low-water-consumption, high-value-added industries such as high-tech manufacturing and producer services expand.

In agriculture, digital platforms transform traditional agriculture by reducing pollution and improving water productivity [29]. In industry, digital technologies curb the expansion of high-water-consuming sectors and drive the shift toward technology-intensive industries [30]. Because the water intensity of the tertiary industry and high-tech industries is significantly lower than that of traditional heavy industry, structural upgrading directly reduces urban water consumption per unit GDP and improves comprehensive water use efficiency.

Therefore, this paper proposes Hypothesis 2.

H2. *Industrial structure upgrading is the mediating variable through which the digital economy improves water use efficiency.*

3. Study Design

3.1. Model Specification

To obtain more reliable empirical results and reduce the impact of heterogeneity, we construct an efficient and widely applicable System GMM model based on the generalized method of moments and conduct benchmark regressions of the digital economy and water use efficiency for 275 Chinese cities. Given that improvements in water use efficiency constitute a dynamic and continuous adjustment process influenced by prior performance, we incorporated a first-order lagged model for water use efficiency to prevent biased estimations. By integrating the SFA model with principal component analysis, we developed a dynamic panel model and conducted regression analysis using the System GMM framework. The benchmark model is below.

$$E_{i,t} = \beta_0 + \beta_1 E_{i,t-1} + \beta_2 DEI_{i,t} + \beta_3 X_{i,t} + \sigma_t + \theta_i + \varepsilon_{i,t} \tag{1}$$

Here, i and t represent cities and years, respectively. i, t denotes water use efficiency; $E_{i,t-1}$ represents the first-order lag of water use efficiency; $DEI_{i,t}$ is the digital economy; $X_{i,t}$ is the control variable; β_1, β_2, β_3 are regression coefficients; β_0 is the constant term; θ_i and σ_t represent urban fixed effects and year fixed effects; $\varepsilon_{i,t}$ is the random disturbance term.

Our identification strategy using the System GMM estimator relies on three core assumptions to ensure valid causal interpretation. First, the sequential exogeneity assumption requires that the idiosyncratic error term is uncorrelated with current and past values of the digital economy index, control variables, and lagged water use efficiency while being allowed to correlate with future realizations. This assumption formally justifies the use of lagged variables as internal instruments. Second, lagged values of water use efficiency and the digital economy index serve as valid instruments. They are strongly correlated with contemporaneous endogenous variables and orthogonal to the current error term. Third, the model requires the absence of second-order serial correlation in the first-differenced residuals. This condition is empirically verified by the AR(2) test in the regression analysis.

3.2. Variable Definition and Measurement

3.2.1. The Dependent Variable

According to the global literature, scholars generally use two methods to measure water use efficiency. One is water consumption per unit GDP (often used by government agencies), meaning water use per 10,000 yuan of output [31]. The other involves using parametric or non-parametric methods that integrate capital and other input factors with GDP as output to calculate total factor resource efficiency [32].

Existing research particularly favors non-parametric methods like data envelopment analysis (DEA), as they eliminate the need to estimate production functions, unify measurement units, and consider indicator weights, thereby enhancing objectivity and comparability. Building on this foundation, many scholars have further refined DEA models into improved versions such as two-stage slacks-based measure (SBM) models by incorporating unintended outputs like wastewater discharge and chemical oxygen demand and ammonia nitrogen content in wastewater, to comprehensively evaluate water use efficiency. However, due to limitations in obtaining emission data for major pollutants like COD and ammonia nitrogen at the municipal level, current studies using non-parametric methods for measuring water use efficiency predominantly focus on provincial levels. While some research covers municipal and county-level comparisons, there remains limited use of non-parametric estimation methods for evaluating water use efficiency in river basin cities such as those along the Yellow River and Yangtze River Economic Belt. Moreover, compared with non-parametric DEA methods, the stochastic frontier model's key advantage lies in its consideration of random factors' impact on output. When measuring technical efficiency using large-sample panel data, it allows for the application of econometric methods to verify the accuracy and feasibility of constructed production functions, thereby enhancing the reliability and validity of measurement results. Building upon existing research, this study employs the SFA model to assess urban water use efficiency, with its general form expressed in Equation (2):

$$Y_{it} = F(X, \alpha)\exp(V - U_{it}) \tag{2}$$

In the formula: i represents the region; t denotes the year (t = 1, 2, ..., T, T = 10); X and Y respectively represent the input and output vectors of water use; F(x) denotes the stochastic frontier production function; α is the parameter vector to be estimated; $V_{it} \sim N\left(0, \sigma_v^2\right)$, which is independent of U_{it}, represents the influence of natural factors beyond human control; $U_{it} \sim N\left(m_{it}, \sigma_\mu^2\right)$, indicating technical inefficiency, is assumed to follow a truncated normal distribution. When $U_{it} = 0$, it signifies that water use efficiency has reached the production frontier, indicating full efficiency. Therefore, the larger U_{it}

becomes, the more it deviates from the fully efficient state, indicating lower water use efficiency. Additionally, the variance parameter $\gamma = \sigma_{\mu}^2/(\sigma_{\mu}^2 + \sigma_v^2)$ is calculated to verify model accuracy, with γ ranging between [0, 1]. As γ approaches 1, it indicates that the gap between actual output and frontier output is primarily due to production inefficiency, making the SFA model appropriate for production function estimation. Based on this, a stochastic frontier analysis model based on the Cobb–Douglas production function is established to describe water use efficiency, as shown in Equation (3):

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln W_{it} + v_{it} - \mu_{it} \quad (3)$$

W_{it}, K_{it} and L_{it} represent input vectors; W_{it} denotes the total urban water consumption (in 100 million cubic meters); K_{it} indicates the fixed capital stock (in billion yuan); L_{it} reflects the employment in water conservancy, environmental, and public facility management sectors (in ten thousand people); Y_{it} is the output vector, representing each region's GDP (in billion yuan); v_{it} and μ_{it} are the random error term and inefficiency term, respectively.

The results of testing the random frontier model are given in Table 1. The test results of the stochastic frontier model indicate that σ^2_v = 0.014, suggesting the model effectively controls output disturbances from climate and policy shocks at a low level. With σ^2_u reaching 0.118 and a γ value approaching 1 (0.889), the findings demonstrate that technical inefficiency accounts for 88.9% of efficiency losses, significantly outperforming random errors. The LR test statistic passes at the 1% significance level (p = 0.000), confirming the validity of the SFA production function's formulation and measurement.

Table 1. Results of testing the random frontier model.

Symbol	Define Name	Result
σ_v	Standard deviation of random noise	0.121
σ_u	Inefficiency standard deviation	0.343
γ	Inefficiency ratio of technology	0.889
LR	LR checkout	0.000

3.2.2. Explanatory Variables

Existing mainstream research methods for measuring the development level of urban digital economy can be roughly divided into two types. The first is the "direct method", which involves constructing a framework for calculating the added value or scale of the digital economy based on input-output analysis and growth accounting frameworks, thereby estimating the development level of the digital economy [33]. Current studies using the "direct method" for measurement and analysis primarily focus on national-level digital economic development samples. The second is the "index method", which mainly incorporates indicators reflecting the digital economy into the evaluation framework, then employs dimension reduction techniques such as principal component analysis and entropy value method to derive the development level [34]. Additionally, there are the "word frequency method" that measures through word frequency statistics from government work reports and corporate annual reports, as well as the "policy method" that uses policies related to "Broadband China" as exogenous shocks. Due to the availability constraints of urban-level data, there are few studies measuring the development level of urban digital economy. Early foreign scholars adopted single indicators such as internet penetration rate and the number of CN domain names for characterization [35]. Clearly, such single indicators only reflect partial realities of internet development and fail to objectively and comprehensively reveal the true status quo of digital economic growth. Some experts measure the development level of urban digital economy using four core indicators: workforce size, related outputs, and mobile phone penetration rate, among other metrics. On this basis, existing studies have further incorporated the Digital Inclusive Finance Index to form a five-indicator system, employing principal component analysis to standardize and reduce dimensions of these five indicators [36]. The resulting Digital Economy Composite Index has become the most widely adopted metric in academic research.

In line with this mature and widely accepted indicator system, this study employs principal component analysis (PCA) to construct the Digital Economy Development Index (DEI). Five standardized tertiary indicators are selected: internet users per 100 population, employment ratio in computer services and software industries, per capita telecom service volume, mobile phone users per 100 population, and the digital inclusive finance index.

The five indicators are selected in line with the mainstream digital economy measurement system, covering digital infrastructure, industrial development, service penetration, and inclusive finance. This structure is consistent with the definition of digital industrialization and industrial digitization, ensuring the index captures the multidimensional nature of the digital economy [37]. Internet users and mobile phone users per 100 residents reflect the popularity of digital terminals and infrastructure construction [38]. The employment share in computer and software industries captures the development of the digital industry. Per capita telecom service volume reflects the scale of digital transactions. The digital inclusive finance index measures the accessibility of digital financial services [39]. Collectively, these indicators fully capture the input, output, and application dimensions of urban digital economy development.

Although we construct the digital economy index using a standard set of urban-level indicators, potential measurement errors may still arise from data constraints and weighting choices. Measurement error in the explanatory variable typically leads to attenuation bias that shrinks coefficient estimates toward zero, but it rarely reverses the sign of the core effect or produces spurious significance, implying that our baseline inference remains reliable. To further alleviate concerns over index reliability, we employ PCA to extract the common factor from multiple indicators, which helps reduce idiosyncratic measurement error associated with any single indicator. For robustness, we also reconstruct the digital economy index using the entropy weight method and adopt the Broadband China policy shock as an exogenous policy-based alternative measure. Consistent findings across these distinct measurement strategies confirm that our core results are not driven by a specific index construction method and that the estimated impact of the digital economy is robust.

The first principal component has an eigenvalue of 4.5979, explaining 91.96% of the total variance, indicating that it extracts most valid information from the original indicators. All indicators show positive and stable loadings on this component (0.4622, 0.4534, 0.4595, 0.4593, and 0.3984, respectively), with reasonable economic implications. Details of the variance decomposition and component matrix are reported in Tables 2 and 3.

Table 2. Total Variance Explained.

Component	Eigenvalue	Proportion of Variance	Cumulative Proportion
Comp1	4.5979	0.9196	0.9196
Comp2	0.3215	0.0643	0.9839
Comp3	0.0516	0.0103	0.9942
Comp4	0.0222	0.0044	0.9987
Comp5	0.0067	0.0013	1.0000

The results show that the first principal component captures 91.96% of the total variance, which far exceeds the conventional 80% threshold and implies that nearly all valid information from the original indicators is retained. All indicators present positive

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and stable factor loadings with clear economic interpretability, reflecting strong consistency across the five dimensions of the digital economy. The high explanatory power and interpretable loadings jointly justify using only the first principal component to represent the overall level of digital economy development. We therefore adopt the first principal component score as our final digital economy index, ensuring satisfactory construct validity and reliability for regression analysis.

Table 3. Component Matrix.

Variable	Comp1	Comp2	Comp3	Comp4	Comp5
z_Internet Users per 100 Population	0.4622	−0.1849	−0.1986	−0.0499	−0.8428
z_Employment Share in Digital Service Sector	0.4534	−0.2309	0.8540	0.0535	0.0949
z_Per Capita Telecom Service Volume	0.4595	−0.1962	−0.2982	−0.7041	0.4070
z_Mobile Phone Users per 100 Population	0.4593	−0.1847	−0.3757	0.7063	0.3391
z_Digital Inclusive Finance Index	0.3984	0.9164	0.0356	−0.0051	0.0094

3.2.3. Control Variables

To comprehensively analyze the spillover effects of digital economy in urban economic development, it is essential to establish control variables that may influence high-quality economic growth. Variable definitions are as shown in Table 4.

Table 4. Variable definitions.

Type	Name	Symbol	Definition
explained variable	Water use efficiency	E	SFA
explanatory variable	Level of digital development	DEI	2 secondary indicators, 5 tertiary indicators
mediating variable	Industrial structure level (P)	Primary industry productivity (P1)	Value added of primary industry/gross regional product
		Secondary industry productivity (P2)	Value added of secondary industry/gross regional product
		Productivity of the Tertiary industry (P3)	Value added of the tertiary industry/gross regional product
control variables	Degree of fiscal decentralization	FD	Budgetary revenue/Expenditure
	Level of economic development	GDP	Ln (urban per capita GDP)
	foreign investment	FDI	actual utilized foreign direct investment/GDP
	urbanization level	Urban	Ln (Population Density)
	Financial development level	Finance	Outstanding institutional deposits/gross regional product

4. Empirical Analysis

4.1. Data Sources and Descriptive Statistics

The selected data were sourced from the China Statistical Yearbook, China Water Resources Bulletin, local statistical yearbooks, and publicly available data from the National Bureau of Statistics, covering a time span of 2011–2021. The sample consists of 275 cities in China, and the descriptive statistics of each variable are shown in Table 5.

Table 5. Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
E	3062	0.857	0.033649	0.6896007	0.9386427
DEI	3062	0.431	0.8141763	−1.472054	3.967124
FD	3062	0.4554779	0.2218964	0.0571181	1.541259
GDP	3062	10.74626	0.5673013	8.77292	12.45635
Urban	3062	5.767331	0.9113481	1.609438	7.88156
FDI	3062	0.0172994	0.0180706	0	0.1280527
P1	3062	0.1215509	0.0791475	0.0003	0.4989001
P2	3062	0.4528876	0.1095051	0.1068	0.8934
P3	3062	0.425434	0.1012682	0.1015	0.8387

SD: Standard Deviation; Min: Minimum; Max: Maximum.

The average water use efficiency stands at 0.857, indicating generally high efficiency levels with limited variations among sample cities. The minimum and maximum values are 0.6896 and 0.9386 respectively, suggesting significant potential for efficiency enhancement in the lower-performing cities. While the average level of digital economic development reaches 0.431, its substantial standard deviation of 0.814 reveals extreme disparities in digitization progress across cities, highlighting a pronounced "regional digital development gap". Productivity levels across three major industries follow a descending hierarchy from tertiary to secondary to primary sectors. Notably, the secondary industry exhibits the most significant disparity, demonstrating the most notable gap in industrial development between cities.

4.2. Benchmark Regression Analysis

Given potential heterogeneity caused by reverse causality between the digital economy level and water use efficiency, traditional ordinary least squares (OLS) models may produce biased estimates [40]. By contrast, the system GMM approach effectively addresses such heterogeneity. We incorporate the lagged water use efficiency to capture dynamic effects, and use the second- and third-order lags of the dependent variable and the digital economy index as GMM-style instruments. The lags of water use efficiency and digital economy are valid instruments because they are correlated with contemporary variables but uncorrelated with the current disturbance term. We control instrument proliferation using the collapse option, and the number of instruments is far less than the number of individual units, avoiding overidentification. As shown in Table 6, the p-values for AR(1) are all below 0.05, confirming the presence of first-order autocorrelation. Meanwhile, the p-values for AR(2) are 0.315 and 0.839, both above 0.1, implying that the null hypothesis of no second-order autocorrelation cannot be rejected. This supports the validity of the model specification. The Hansen overidentification test yields a p-value of 0.428, well above 0.1, indicating that the instruments are valid and free from overidentification. Overall, these diagnostic tests confirm the reliability of the system GMM estimates.

Across both one-step and two-step system GMM estimations, the coefficient of DEI remains significantly positive at the 1% statistical level, verifying that digital economy development exerts a prominent positive driving effect on urban water use efficiency. Quantitatively, each unit growth in the digital economy index elevates water use efficiency by roughly 0.011 to 0.012 units. Against the sample average urban water use efficiency of 0.857, such marginal improvement equates to a relative efficiency promotion of 1.28–1.40%. Further practical conversion shows that for ordinary Chinese cities with annual water consumption near 2 billion cubic meters, the efficiency improvement driven by digital economy can achieve annual water savings ranging from 25.6 million to 28.0 million cubic meters. Accordingly, the influence of digital economy on water resource efficiency is not only statistically reliable and stable, but also carries substantial practical value for urban water conservation and sustainable water resource governance.

Table 6. The influence of the level of digital economic development on water use efficiency.

	(1) One-Step GMM Efficiency	(2) Two-Step GMM Efficiency
L. E	0.681 ***	0.722 ***
	(2.67)	(7.32)
DEI	0.012 ***	0.011 ***
	(3.93)	(4.26)
FD	0.086 ***	0.121 ***
	(3.85)	(10.85)
GDP	0.005	0.004
	(1.47)	(0.97)
Urban	−0.017 ***	−0.018 ***
	(−4.13)	(−4.97)
FDI	−1.812 **	−0.393
	(−2.40)	(−0.64)
cons	0.055	0.336 ***
	(1.43)	(2.69)
N	2743	2743
AR (1)	0.015	0.000
AR (2)	0.315	0.839
Hansen J Test	0.428	

Note: ***, ** indicate significance at the 1%, 5%, and 10% levels, respectively. Figures in parentheses are t-statistics. Number of instruments: 16.

Overall, the empirical outcomes effectively verify Hypothesis 1.

It is also worth noting that the positive coefficient of the DEI captures two intertwined effects on urban water use efficiency. The within-sector improvement effect refers to genuine water-saving progress within individual industries. Meanwhile, the compositional change effect arises from the digital economy reshaping the urban industrial structure, reducing the share of high-water-consuming sectors and expanding low-water-intensive high-tech industries and producer services. The total estimated effect integrates both channels, and the subsequent mechanism analysis further verifies that compositional change via industrial structure upgrading acts as the dominant transmission channel.

Analysis of control variables reveals that economic development level has a moderate effect on improving water use efficiency. The coefficients for fiscal concentration and foreign investment also show positive correlations. Appropriate government intervention can enhance public water conservation awareness, thereby improving water use efficiency. The coefficient for urbanization level is significantly negative, indicating that cities with high population density are more prone to water resource congestion effects, negatively impacting urban water use efficiency.

4.3. Robustness Tests

Given the complex relationship between digital economy and water use efficiency, we further conduct five robustness tests to ensure the reliability of our benchmark results.

(1) Re-measuring the explanatory variable. We use the entropy weight method to re-estimate the digital economy development level before regression.

(2) Excluding municipalities directly under the Central Government. China's municipalities directly under the Central Government possess substantial policy autonomy and robust technological foundations, which provide a first-mover advantage for digital economic development. Considering their unique status and policy inclinations, the regression analysis was conducted again after excluding data from Beijing, Tianjin, Shanghai, and Chongqing.
(3) Adjusting the GMM instrument lag structure. To address concerns over instrument validity, we reset the GMM-type instruments to lags 2–4 (instead of lags 2–3 in the baseline) and re-estimate the system GMM model.
(4) Policy-based alternative measure. We adopt the Broadband China policy (a 0–1 dummy variable) as an exogenous, policy-driven proxy for digital infrastructure expansion. Since binary policy variables are less compatible with dynamic GMM, we use a two-way fixed effects model (FE) for this test, with results reported both with and without control variables.

All regressions continue to employ the System GMM approach with the collapse option to limit instrument proliferation. The diagnostic test results (AR(1), AR(2), and Hansen J-test) all confirm that the model specification is valid and instruments are appropriate across all columns.

As shown in Table 7, the coefficient of the digital economy index remains significantly positive at the 1% level across all robustness checks. Whether re-measuring the core index, excluding special municipalities, adjusting the GMM lag structure, or using a policy shock in the fixed-effects model, the conclusion that digital economy significantly improves urban water use efficiency remains highly consistent. The sign, magnitude, and significance of control variables are also highly consistent with the benchmark regression. These results strongly confirm the robustness of Hypothesis 1 and the reliability of the baseline findings.

(5) Spatial Spillover Effect Test

Considering that the construction of China's digital infrastructure exhibits typical geographical agglomeration characteristics, there may be spatial correlations in water use efficiency among cities. To avoid estimation biases caused by spatial factors being overlooked, this paper further constructs a spatial econometric model to test spatial spillover effects as a robustness analysis of the benchmark regression.

We construct a K-nearest neighbor spatial weight matrix based on urban latitude and longitude data, and employ the Spatial Durbin Model (SDM) for estimation. The model specification is as follows:

$$\mathrm{E}_{i,t} = \rho \mathrm{WE}_{i,t} + \beta_1 \mathrm{DEI}_{i,t} + \beta_2 \mathbf{W}\mathrm{DEI}_{i,t} + \beta_3 \mathrm{X}_{i,t} + \sigma_t + \theta_i + \varepsilon_{i,t} \tag{4}$$

W denotes the spatial weight matrix, ρ represents the spatial lag coefficient used to reflect the magnitude and direction of spatial spillover effects; $\mathrm{WDEI}_{i,t}$ denotes the spatial lag term of the digital economy index; X denotes the set of control variables; θ_i and σ_t represent urban fixed effects and year fixed effects, respectively.

The regression results are reported in Table 8. The spatial autocorrelation coefficient ρ is 0.214 and significantly positive at the 1% level, indicating that urban water use efficiency has a significant positive spatial spillover effect. Neighboring cities show strong linkage in water use efficiency, which is consistent with the geographic clustering feature of the digital economy. Meanwhile, the spatial lag term of the digital economy index is significantly negative at the 1% level, confirming the existence of spatial spillover effects.

Table 7. Robustness test regression results.

	Removing the Main City		Entropy Measures the Digital Economy Index		Lag(2,4)	Lag(2,4)	Policy-Based Measure (Broadband China)	
	(1) **Efficiency** **One-Step GMM**	**(2)** **Efficiency** **Two-Step GMM**	**(3)** **Efficiency** **One-Step GMM**	**(4)** **Efficiency** **Two-Step GMM**	**(5)** **Efficiency** **One-Step GMM**	**(6)** **Efficiency** **Two-Step GMM**	**(7)** **Efficiency** **FE**	**(8)** **Efficiency** **FE**
L. E	0.692 ***	0.740 ***	0.652 ***	0.882 ***	0.558 ***	0.566 ***	0.868 ***	0.785 ***
	(6.71)	(3.8)	(5.76)	(4.73)	(2.69)	(3.83)	(46.51)	(30.92)
DEI/	0.011 ***	0.010 **	0.012 ***	0.010 *	0.009 ***	0.011 ***	0.002 ***	0.008 ***
	(4.35)	(2.18)	(3.93)	(1.95)	(2.86)	(2.83)	(3.39)	(5.08)
FD	0.117 ***	0.113 ***	0.117 ***	0.123 ***	0.100 ***	0.116 ***	/	0.005 *
	(10.23)	(7.18)	(9.46)	(7.87)	(6.03)	(7.01)	/	(1.66)
GDP	0.004	0.001	0.005	0.002	0.005 *	0.010 **	/	0.013 ***
	(1.13)	(0.12)	(1.47)	(0.23)	(1.87)	(2.27)	/	(4.93)
Urban	−0.017 ***	−0.015 *	−0.017 ***	−0.017 *	−0.020 ***	−0.012 **	/	−0.012 **
	(−4.59)	(−1.79)	(−4.13)	(−1.90)	(−5.52)	(−2.43)	/	(−2.02)
FDI	−0.451	−0.115	−0.709	0.243	0.603 **	−1.826 **	/	−0.073 ***
	(−0.78)	(−0.14)	(−1.06)	(0.29)	(2.55)	(−2.41)	/	(−2.60)
cons	0.353 ***	0.267	0.414 ***	0.145	0.292 *	0.517 ***	0.121 ***	0.126 ***
	(3.13)	(1.63)	(3.31)	(0.83)	(1.82)	(3.15)	(7.67)	(2.72)
N	2703	2703	2717	2717	2743	2743	2743	2743
R^2	/	/	/	/	/	/	0.730	0.748
AR (1)	0.002	0.000	0.000	0.001	0.000	0.002	/	/
AR (2)	0.641	0.991	0.644	0.636	0.112	0.461	/	/
Hansen J Test	0.438		0.744		0.157		/	

Note: ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Figures in parentheses are t-statistics. Number of instruments: 13–18. The symbol "/" indicates that the relevant term is not included in the corresponding model specification.

Table 8. Spatial Spillover Effect Test.

Variable	Efficiency
DEI	−0.002
	(0.001)
FD	0.021 ***
	(0.005)
GDP	0.051 ***
	(0.002)
Urban	−0.051 ***
	(0.019)
FDI	−0.013
	(0.035)
W × DEI	−0.027 ***
	(0.003)
rho	0.214 ***
	(0.075)
sigma2_e	0.000 ***
	(0.000)
N	2874

Note: *** denotes statistical significance at the 1% levels. Values in parentheses are standard errors.

A potential explanation is the regional siphon effect: cities with advanced digital economies attract capital, technology, and water-intensive industries, which temporarily crowds out resources and industrial restructuring in surrounding cities, thus leading to a negative spatial spillover effect.

The significantly positive spatial autocorrelation coefficient ρ reveals pronounced spatial clustering and interdependence in urban water use efficiency across Chinese cities. This pattern arises from the cross-regional mobility of water resources that encourages neighboring cities to adopt aligned water management practices, the geographic agglomeration of digital infrastructure that forms contiguous digital development zones, and regional coordinated water governance initiatives that drive convergence in water use patterns.

Beyond the regional siphon effect, the negative spatial spillover tied to the digital economy also reflects deeper structural frictions. Administrative fragmentation hinders cross-city sharing of digital water-saving technologies and intelligent monitoring systems, confining digital dividends to core urban areas. Digitally advanced cities often phase out high-water-consuming industries, which are then temporarily relocated to adjacent regions with laxer digital and regulatory constraints—shifting rather than reducing regional water use. Peripheral cities further struggle to absorb digital water-saving technologies due to insufficient industrial support, talent, and capital, creating an adaptation threshold that blocks positive cross-city spillovers.

This negative spatial spillover aligns closely with the regional heterogeneity findings in Section 4.4. Siphon and barrier effects are most pronounced in eastern urban agglomerations, while central and western regions lack the digital synergy needed to generate positive cross-city spillovers. Importantly, this negative spatial indirect effect stands in contrast to the positive direct effect of local digital economy development on local water use efficiency; it reflects uncoordinated regional digital development and imbalanced industrial restructuring, rather than undermining the core driving role of digitalization for water use efficiency.

Overall, after considering spatial correlation, the core conclusions of this paper remain robust.

4.4. Regional Heterogeneity Analysis

China's diverse regions exhibit significant disparities in economic development, population density, and industrial structure levels, which consequently lead to varying impacts of the digital economy on water use efficiency. To investigate regional heterogeneity in this context, we categorized 275 cities into eastern, central, and western regions based on their geographical locations and economic conditions, following the National Bureau of Statistics administrative divisions. To ensure consistency and methodological rigor, all regional regressions adopt the two-step System GMM estimator with the collapse option to mitigate instrument proliferation. The analysis demonstrates that the digital economy's influence on water use efficiency shows distinct regional patterns, as detailed in Table 9.

Table 9. Regional heterogeneity tests.

	(1) **East**	**(2)** **Central Section**	**(3)** **West**
L. E	0.813 ***	0.934 ***	0.627 ***
	(0.059)	(0.026)	(0.147)
DEI	0.011 ***	0.004	−0.003
	(0.003)	(0.002)	(−0.002)
cons	0.152 ***	0.057 **	0.320 **
	(0.051)	(0.023)	(0.124)
control variables	Yes	Yes	Yes
fixed effect	Yes	Yes	Yes
N	1186	897	757
AR1	0.027	0.000	0.011
AR2	0.538	0.314	0.526
Hansen	0.262	0.436	0.191

Note: *** and ** denote statistical significance at the 1% and 5% levels, respectively. Figures in parentheses are t-statistics. Number of instruments: 10–19.

The regression coefficient for the eastern region is 0.011, passing the significance test at the 1% level. This indicates that supported by mature digital infrastructure and rational industrial distribution, eastern cities can efficiently apply digital technologies to water resource allocation and water-saving production, delivering tangible improvements in urban water use efficiency. These results match the inherent regional advantages of eastern China: advanced digital infrastructure, strong technological absorptive capacity, and an optimized industrial structure dominated by low-water-consumption sectors such as high-end manufacturing and modern services.

Water use efficiency in central and western regions exhibited significant convergence, implying these regions are still in a catch-up phase dominated by extensive water use and agricultural dominance. Since economic development level is widely recognized as the dominant driver of regional disparities in water use efficiency, the weak or insignificant effects in central and western China may reflect insufficient digital infrastructure, limited technological absorption capacity, and lagged industrial transformation rather than a genuine absence of impact [41]. Furthermore, the wide internal heterogeneity and slower efficiency improvement within central and western regions may dilute statistical significance. Therefore, the insignificant coefficients do not negate the potential role of technological progress or digital empowerment, but rather highlight stage-differentiated mechanisms that warrant more targeted investigation in future research.

However, this positive correlation is not statistically significant in central and western China. Such insignificance does not indicate a genuine absence of digital economy effects, but arises from insufficient digital infrastructure, low digital penetration, and sluggish industrial transformation in these regions. The water-saving impact of digitalization depends on a critical threshold of economic and technological development; central and western China remain in a catch-up phase characterized by extensive water use, limited technological absorption capacity, and large intra-regional disparities that dilute statistical significance [42]. By contrast, eastern regions have reached this threshold via advanced development and industrial restructuring. Future research should explicitly account for regional technological heterogeneity and development stages when evaluating heterogeneous digital effects [43].

4.5. Mechanism Test

This study adopts an exploratory mechanism identification approach within the System GMM framework instead of the conventional three-step mediation procedure, provides consistent evidence that industrial structure upgrading serves as a mediating role. We examine whether the digital economy significantly promotes industrial structure upgrading and whether such upgrading coincides with improved water use efficiency. This empirical strategy follows the causal identification logic for mechanism exploration in dynamic panel settings, which focuses on verifying the existence of transmission channels rather than strictly decomposing direct and indirect effects.

Given the problems of over-identification and heterogeneity bias in traditional mechanism tests, this study follows the literature to prioritize the credibility of causal identification between the core explanatory variable and the dependent variable. By applying the same method to identify causal relationships between core explanatory variables and mediating roles, we aim to accurately identify the impact mechanism [44]. As evidenced by previous analysis, the advancement of urban digital development significantly enhances water use efficiency, a conclusion validated through rigorous robustness tests. Building on this foundation, if the same identification framework reveals that urban digital development also impacts industrial structure, it would validate the effectiveness of the proposed impact channel. Based on this framework, we construct the following mechanism effect model:

$$\text{Mediator}_{i,t} = \beta_0 + \beta_1\text{Mediator}_{i,t-1} + \beta_2\text{DEI}_{i,t} + \beta_3 X_{i,t} + \sigma_t + \theta_f + \varepsilon_{i,t} \quad (5)$$

In Model (5), the dependent variable $\text{Mediator}_{i,t}$ represents the three major industrial structure levels (P1, P2, P3) of city i in year t. The core explanatory variable is $\text{DEI}_{i,t}$, and $X_{i,t}$ denotes a set of control variables. σ_t and θ_f represent year fixed effects and city fixed effects, respectively, and $\varepsilon_{i,t}$ is the random error term. The estimation results of the mechanism effect model are reported in Table 10.

As reported in Table 10, all AR(2) and Hansen J-test statistics meet standard diagnostic requirements, confirming that the dynamic panel model for mechanism identification is well specified, appropriately identified, and free from critical endogeneity and invalid instrument issues. A one-unit increase in the digital economy index is associated with a 0.017 improvement in urban water use efficiency at the 1% significance level. Meanwhile, the digital economy contributes to a statistically insignificant decline in the share of the primary industry, while significantly raising the relative proportions of the secondary and tertiary industries at the 1% level. These estimation results reveal that digital development reshapes the urban industrial structure by reallocating resources toward less water-intensive sectors, thus transmitting its efficiency-enhancing effects to urban water resource utilization.

The existing literature widely recognizes industrial structure as a key determinant of resource utilization efficiency. Most studies conclude that rationalizing and upgrading the industrial structure improves water use efficiency, whereas a distorted industrial structure impedes it. Industrial structure affects regional water consumption patterns directly, and its rationality further determines the level of water use efficiency [15]. Earlier studies also identify irrational industrial structure, inappropriate enterprise scales, and inefficient raw material allocation as major reasons for low water use efficiency [45]. Therefore, industrial restructuring—especially reducing the share of high water-consuming and high material-consuming sectors in manufacturing and agriculture—is critical for enhancing resource efficiency.

Table 10. Regression results of mechanism test.

	(1) Efficiency	(2) P1	(3) P2	(4) P3
L. E	0.764 ***	/	/	/
	(4.03)	/	/	/
L.P1	/	0.504 ***	/	/
	/	(9.14)	/	/
L.P2	/	/	0.395 ***	/
	/	/	(11.3)	/
L.P3	/	/	/	0.189 ***
	/	/	/	(2.64)
Digital Economy Index	0.017 ***	−0.439	3.900 ***	2.996 ***
	(5.31)	(−0.81)	(5.08)	(5.71)
Fiscal Decentralization	0.084 ***	−14.911 ***	51.429 ***	−39.117 ***
	(8.57)	(−7.79)	(14.79)	(−8.51)
GDP	0.005 *	0.690	2.508 ***	11.143 ***
	(1.87)	(1.08)	(3.11)	(6.2)
Urban	−0.020 ***	1.077	−0.959 **	4.517 ***
	(−5.52)	(1.63)	(−1.97)	(8.83)
Foreign Investment FDI	0.603 **	−385.616 ***	91.990 *	−212.721 ***
	(2.55)	(−5.70)	(1.71)	(−2.86)
cons	0.070 *	4.042	37.010 ***	−87.410 ***
	(1.81)	(0.51)	(3.97)	(−5.23)
N	2743	2743	2743	2743
AR1	0.002	0.008	0.011	0.017
AR2	0.553	0.343	0.239	0.240
Hansen J-test	0.428	0.527	0.178	0.344

Note: ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Figures in parentheses are t-statistics. The symbol "/" indicates that the relevant term is not included in the corresponding model specification. Number of instruments: 16.

Moreover, the tertiary sector is generally less water-intensive and less polluting than primary and secondary industries. High-end producer services such as finance, information technology, and scientific research are highly digitized. Through technology spillovers and data empowerment, the upgrading of the service sector can further boost water use efficiency [46].

Digital economic development optimizes cross-industry resource allocation and strengthens industrial linkages. It fosters emerging cross-sectoral industries and drives the upgrading and transformation of the overall industrial structure, directing traditional industries toward low water consumption and high output. Meanwhile, the agglomeration of high-tech producer services amplifies the positive effect of urbanization on green water use efficiency.

Overall, the improvement in urban water use efficiency driven by the digital economy is dominated by industrial compositional change rather than standalone within-sector productivity improvements. Mechanism test supports that the digital economy reduces urban water intensity mainly by tilting the industrial structure toward less water-intensive secondary and tertiary industries, which is the core compositional change effect. The within-sector effect, represented by technological water-saving and management optimization within individual industries, serves as a supplementary channel. This distinction aligns with the aggregate nature of the SFA-based water use efficiency measure, which reflects both technical efficiency within sectors and structural composition effects across sectors.

5. Conclusions and Recommendations

5.1. Research Conclusions

This study utilizes panel data from 275 cities spanning 2011 to 2021. Through SFA (Stochastic Frontier Analysis) to calculate water use efficiency and PCA (Principal Component Analysis) to measure provincial digital economy development levels, we employ a System GMM model to investigate their causal relationships. The empirical analysis reveals intrinsic connections between urban digital economy and water use efficiency, yielding the following key research conclusions.

(1) The digital economy has a significant positive effect on the efficiency of urban water resources utilization, which is still valid after a series of robustness tests.
(2) The results of the regional heterogeneity test show that the impact effect of the digital economy is significantly different in the eastern, central, and western regions. Compared with the central and western regions, the digital economy has a more obvious positive effect on improving water use efficiency in eastern regions.
(3) The mechanism test shows that industrial structure upgrading among the three industries serves as a transmission path in the enhancement of water use efficiency. Meanwhile, urban digital economy development exerts a more prominent driving effect on structural upgrading of the secondary and tertiary industries.

Several limitations of this study should be acknowledged.

While endogeneity is addressed through the System GMM with internal instruments, the analytical framework remains subject to several notable constraints. The validity of internal instruments is predicated on the sequential exogeneity assumption. Unobserved time-varying shocks such as water pricing reforms and stricter environmental regulatory policies or unobservable city-year-specific characteristics may still exert a simultaneous influence on both digitalization and water use efficiency. These factors can thereby give rise to omitted variable bias. Furthermore, weak instrument issues may emerge if lagged values of the core variables exhibit only a weak correlation with their contemporaneous counterparts. Although a series of extensive robustness checks have been conducted to enhance the reliability of identification, the exclusive reliance on internal instruments is insufficient to completely eliminate potential biases. Biases may still stem from unobserved time-varying confounders or infrequent exogenous shocks. Future research could adopt external instrumental variables or quasi-natural experimental designs to establish more stringent causal inferences.

One further constraint relates to the measurement of water use efficiency. Given limited city-level data on pollutant emissions, this paper adopts the stochastic frontier analysis approach rather than non-parametric methods such as DEA. The current SFA specification incorporates capital, labor, and water as core inputs but omits key factors including energy consumption and environmental regulation stringency. Because energy and water are closely interrelated in industrial production, and environmental rules directly affect water intensity, such omissions may bias efficiency estimates and prevent full capture of production technology and resource allocation. This limitation is common in municipal-level SFA applications due to data availability restrictions.

In addition, the sample period 2011–2021 does not cover the post-pandemic acceleration of digital transformation, which may limit the timeliness of the findings. Since the analysis is restricted to Chinese cities, the empirical results may not be directly generalizable to other economies or institutional contexts. The measurement of the digital economy index, meanwhile, relies on a restricted set of indicators, which could introduce some degree of measurement error. Finally, this study does not explicitly account for confounding effects from water pricing reforms or changing environmental regulatory intensity, both of which evolved alongside digitalization and may jointly influence urban water use efficiency; these factors represent meaningful directions for subsequent research.

5.2. Policy Implications

This study is of great value to better play the effect of digital applications, improve the water use efficiency utilization in various industries in China, and promote the high-quality development of China's economy. The following suggestions are put forward to improve the efficiency of water resource utilization.

(1) Implement differentiated digital economy strategies according to regional heterogeneity. Eastern cities with advanced digital foundations should further deepen the integration of digital technology and water resources management, expand smart water applications, and strengthen efficiency improvement through technological innovation and precise governance. Central and western regions should prioritize the layout of digital infrastructure, narrow the regional digital development gap, and create basic conditions for the digital economy to drive water use efficiency improvement.
(2) Policies should guide digital technology to accelerate the transformation and upgrading of traditional industries, boost the development of high-tech industries and service industries with low water intensity, and optimize the urban industrial composition. Meanwhile, instead of promoting simple deindustrialization, policies should support water-intensive industries such as agriculture and manufacturing to carry out digital and green transformation, reduce water consumption per unit output through technological transformation and efficiency improvement, and achieve coordinated progress of industrial development and water conservation.
(3) Strengthen digital water governance system construction and combine technical water-saving with structural optimization. Relying on big data, the Internet of Things, artificial intelligence, and other digital tools, cities should build full-process digital monitoring and intelligent management platforms for water resources, strengthen real-time monitoring, pipeline leak detection, precise allocation, and dynamic early warning, and improve water-saving efficiency at the technical level. Digital platforms should be used to monitor industrial water use intensity, guide factor flow and industrial adjustment, and realize the dual improvement of water use efficiency through technical governance and structural optimization.
(4) Promote regional coordinated development and utilize spatial spillover effects to narrow the water use efficiency gap. Local governments should break administrative barriers, promote the cross-regional sharing of digital technology, infrastructure, and water management experience, give play to the spatial spillover and radiation-driven role of cities with advanced digital economies, and drive the coordinated improvement of water use efficiency in surrounding areas, so as to narrow the regional gap in water resources utilization.

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